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Improving Analytical Support under Deep Uncertainty

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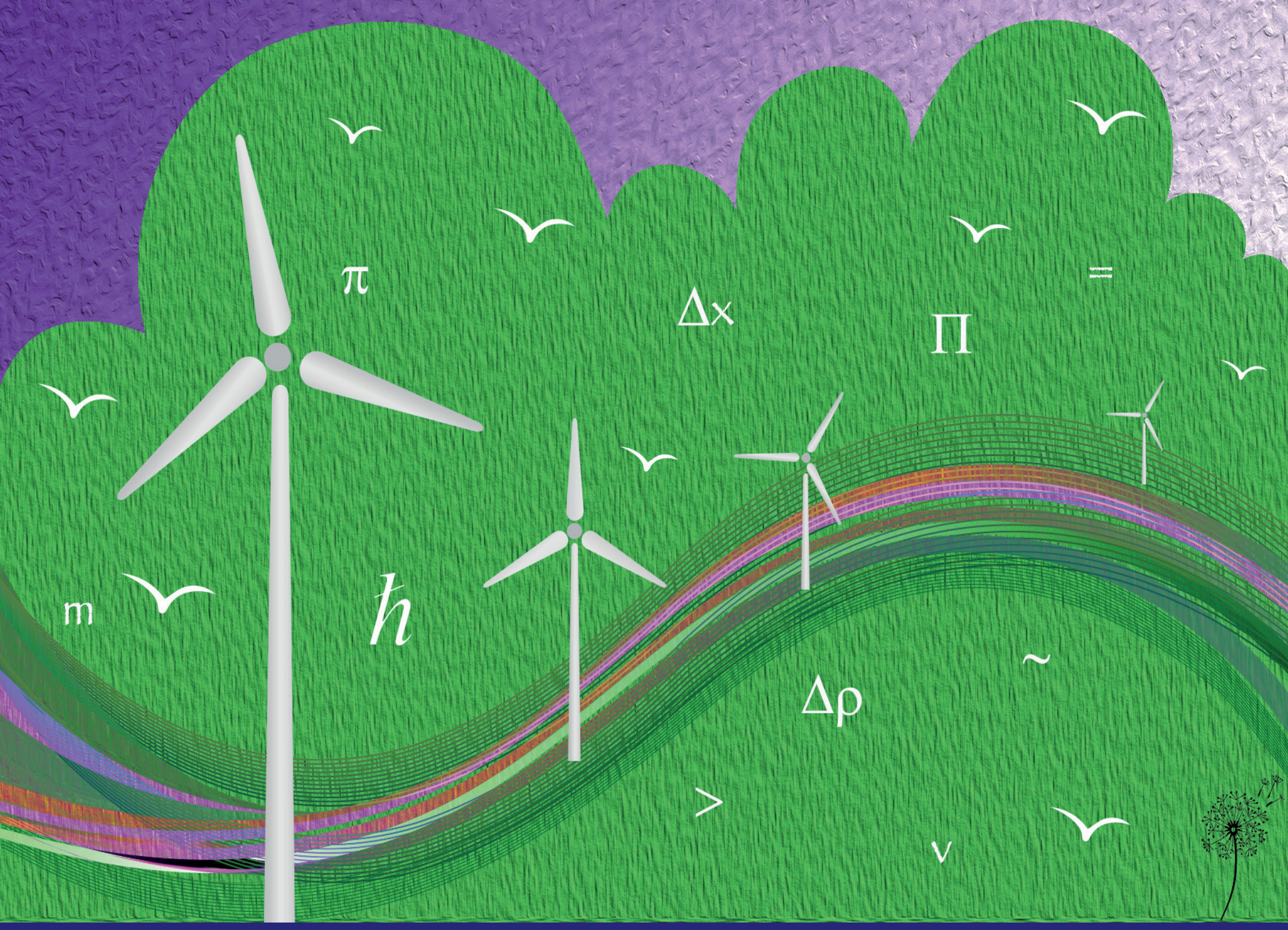

Caner Hamarat

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The Adaptive Robust Design Approach: Improving Analytical Support under Deep Uncertainty

Caner Hamarat

Delft University of Technology

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The Adaptive Robust Design Approach: Improving Analytical Support under Deep Uncertainty

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PREFACE

This thesis has been the final product of the research was primarily conducted between 2010 and 2014, during which the articles that constructs the body chapters of this thesis were published. The chapters of this thesis, which address the methodological questions (Chapter 2, 3 and 4), have been published as research articles between 2010 and 2014 in different journals. We have deliberately chosen to publish distinct chapters of this methodological thesis as timely articles, and made them quickly accessible to the research community. There has been an unanticipated delay that resulted in the thesis-writing period that took longer than expected, which was mainly due to the interruption by starting a new job before finishing the thesis writing. As widely cited journal articles and many conference proceedings independently published from this research raised wide interest, it has been worthwhile to put the final effort to bring them together and complete the writing process. I am glad that this thesis has finally come to an end.

The thesis aims to improve analytical support for policymaking in the presence of deep uncertainty. This thesis provides a comprehensive overview of the articles published during the research period, and makes the developed methodologies more accessible for policy researchers by presenting the complete research as a single thesis.

During the period in which the research was conducted, this study field has been booming and what has been done in the course of this study has contributed to this development. The researchers who work on policymaking under uncertainty have built further research upon these already published articles. Thanks to the researchers in this field, further advancements have been made during the last years that made this line of research more visible and more established.

Chapter 1 - INTRODUCTION

1.1. Policymaking under uncertainty

Policymaking is a process that often involves different parties such as policymakers, stakeholders and analysts. Policy analysts assist policymakers by defining the problem content and by designing and evaluating policy alternatives (Hermans & Thissen, 2009). It is up to the policymakers whether to make use of the guidance provided by the analysts or to design policies by themselves. The policymaking process can be challenging as there are aspects to be considered for any policymaking problem. One is the time horizon, as the nature of policymaking differs for short and long-term issues. Complexity is another important aspect and it is present in almost any decision-making issue. According to Senge (Senge, 1990), there are two types of complexity: detail complexity and dynamic complexity. Detail complexity refers to the sort of complexity where there are many elements in a system, whereas dynamic complexity can be defined as "situations where cause and effect are subtle, and where the effects over time of interventions are not obvious" (Senge, 1990). Most conventional methods are equipped to handle detail complexity but not dynamic complexity. Long-term policymaking is particularly difficult because as the time horizon expands, uncertainty increases. Uncertainty can be defined as "any departure from the unachievable ideal of complete determinism" (Walker, et al., 2003). Uncertainty is not only due to a lack of knowledge, but additional knowledge about unknown aspects can contribute to uncertainty. Shallow uncertainty, where the possibilities and their probabilities are known, is relatively easier to tackle than deep uncertainty, where "analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes" (Lempert, Popper, & Bankes, 2003). There can be different strategies for policymaking that policymakers can follow under uncertainty. Thissen & Agusdinata (2008) categorize four different strategies to deal with uncertainty: (1) ignore uncertainty, (2) delay the decision and wait for uncertainty to be reduced by time, (3) reduce uncertainty, and (4) accept uncertainty and act consciously. These strategies can be used separately or in combination with each other. Ignoring uncertainty can lead to undesirable outcomes, delaying the decision can cause to miss opportunities and reducing uncertainty can be costly due to the actions required for uncertainty reduction such as doing research, buying information, insurance or negotiation with stakeholders. When acting by accepting uncertainty, possible strategies can be to design static decisions that do well in most future conditions or to design adaptive policies that can adapt in time as the future unfolds.

Policymaking under deep uncertainty has emerged as a topic that gets increasing attention in the planning literature. Under deep uncertainty, predictive planning approaches that, in essence, ignore uncertainties, are likely to result in plans that perform poorly. In response, an alternative planning paradigm has emerged. This paradigm suggests that, in the light of deep uncertainty, one needs to plan dynamically and build in flexibility (Albrechts, 2004; Eriksson & Weber, 2008; Lempert, Popper, & Bankes, 2003; Neufville & Odoni, 2003; Schwartz & Trigeorgis, 2004; Swanson et al., 2010; Walker, Rahman, & Cave, 2001). This paradigm can be regarded as an elaboration of the fourth strategy proposed by Thissen & Agusdinata (2008) to deal with uncertainty, which is to accept uncertainty and act consciously.

Two main streams can be distinguished in the literature, we will label them 'adaptive management' and 'planned adaptation'. The core idea of adaptive management is one of trial and error, or, formulated more positively, learning and adaptation. The initial ideas for adaptive management were proposed by Dewey (1927): policies should be treated as experiments, with the aim of promoting continual learning and adaptation in response to experience over time (Busenberg, 2001). Similar ideas can be found in the field of environmental management (Holling, 1978; McLain & Lee, 1996), where policies may be designed from the outset to test clearly formulated hypotheses about the behaviour of an ecosystem being changed by human use (Lee, 1993). A similar attitude is also advocated by Collingridge (1980) with respect to the development of new technologies. Given ignorance about the possible side effects of technologies under development, he argues that one should strive for correctability of decisions, extensive monitoring of effects, and flexibility. There have been attempts to develop structured and stepwise approaches for adaptive management, for example, Brans et al. (1998) proposed an iterative approach that combines System Dynamics, adaptive control theory and multi-criteria decision aid to design and to implement long-term policies for socio-economic systems. All of these approaches have in common that policies or plans are not designed in advance to be adaptive but adaptations are developed as the future unfolds.

Alternatively, in 'planned adaptation' plans are designed where the plan itself already includes specified adaptation actions at certain moments and under certain pre-specified conditions. Scenario Planning (Schoemaker & van der Heijden, 1992) provides a generally well-known example of this approach. Planned adaptation requires thinking ahead to pre-define adaptations at predetermined conditions in time (Kwakkel & Haasnoot, 2019). A further elaboration of this approach proposed by Walker et al. (2001) is called Adaptive Policymaking. This approach advocates that plans should be adaptive: one should preferably take only those actions that are non-regret and time-urgent, and postpone other actions to a later stage so that one can take advantage of information that becomes available in the future. In order to realize this, it is suggested that a monitoring system and a pre-specification of responses when specific trigger values are reached should complement the basic plan (Kwakkel, Walker, & Marchau, 2010).

1.2. Use of mathematical models in policymaking

Using mathematical models as representation of a real world system is a method for analysts to support policymakers with information to develop policies. A mathematical model can be defined as an abstract description of relevant features of a system using mathematical language, where modellers aim to represent these features of real world system in the form of mathematical equations/relations. Such models can be used for studying and understanding the behaviour of a system of interest. Models can have different types of characteristics such as linear, nonlinear, static, dynamic, discrete or continuous. Various tools and techniques are available for building different types of mathematical models. For instance, using spreadsheets (e.g. Microsoft Excel) for building models has been very popular in business. Mathematical models are extensively used in natural sciences and engineering, as well as in the social sciences.

Model(s) can be used for studying a system of interest with different purposes. A common approach is to use models for forecasting the future state of a system. Modellers make assumptions about the real-world system of interest. These assumptions about parameter values, relationships between variables, worldview about the system of interest constitute the model. Since the assumptions used in models incorporate various uncertainties, it is preposterous to conclude that assumptions about the future can be taken as the "truth". For this reason, the use of models with (many) fixed assumptions for predictive purposes should be questioned. Bankes (1993) therefore proposed to use models for decision-making in an explorative manner- exploration of an ensemble of plausible futures. Instead of focusing on best-estimate predictions under uncertainty, the models are used to explore as many plausible futures as possible. This proposal by Bankes (1993) has been picked up many others (Haasnoot et al., 2013; Hamarat et al., 2013; Kwakkel et al., 2010; Lempert et al., 2003; Walker et al., 2001; Walker et al., 2013). Similarly, this thesis adopts Bankes' proposal to use exploratory modeling and builds the methodological developments proposed in this thesis on this explorative approach.

1.3. Recent developments of analytical support in model-based policymaking under deep uncertainty

In recent years, several model-based approaches and methods have emerged to answer the problem of dealing with deep uncertainty in decision-making. At this point, a historical perspective on this thesis and the literature needs to be clarified for the readers. As the research reported on in this thesis has been conducted between 2010 and 2014, the developments in this period occurred in parallel to this thesis. Although the developments after 2014 are not considered in the analysis conducted in this thesis, they are explained here to give a comprehensive understanding and to link this thesis to the current state-of-the-art in the analytical support in model-based policymaking.

Info Gap Theory is a method for analysis, planning, decision and design under uncertainty (Ben Haim, 2006). Info-Gap Theory has three main components: a system model representing the system of interest, an info-gap uncertainty model that quantifies uncertainties in a non-probabilistic way and performance requirements aimed for by decision makers.

Real options analysis (de Neufville & Scholtes, 2011) is another method for tackling uncertainties in engineering design, especially for infrastructure designs or investment decisions. An option is defined as “a right, but not an obligation, to do something under predefined arrangements” similar to the way in which options are used as contracts in financial markets (Neufville, 2003). Real options analysis considers options as physical things (i.e. elements of a system), rather than financial contracts. This method helps to build a flexible plan which treats uncertainty as an opportunity, instead of as risk to avoid, through the use of “real” options (Neufville, 2003). To make use of the flexibility that options can provide, they can be used as elements of an adaptive plan.

Buurman & Babovic (2016) have proposed a systematic methodology to incorporate real options analysis that helps policymakers design adaptive plans in which options are used as elements. In this systematic approach, Buurman & Babovic (2016) combine real options analysis with the Adaptive Policymaking approach which allows analysts to handle uncertainties by creating adaptive policies that are robust across a range of plausible futures.

Robust Decision Making (RDM) (Lempert, Groves, Popper, & Bankes, 2006) has been another approach for developing robust strategies under deep uncertainty. RDM is an iterative, analytic and systematic approach that combines the qualitative part of narrative scenarios and the power of quantitative analysis to support decision-making under deep uncertainty. It has been developed by researchers from the RAND Corporation (Groves & Lempert, 2007). RDM is applied iteratively in four main steps: (1) conceptualization of the system of interest, identification of uncertainties and building simulation model(s), (2) generation of cases by exploring uncertainties, (3) scenario discovery, which is a computer-assisted method to identify relevant or interesting scenarios by using machine learning algorithms, and (4) trade-off analysis for comparing performances of different strategies (Lempert, et al., 2013). RDM aims to provide a ‘robust’ policy design, i.e., a design that performs well across an ensemble of plausible futures, instead of a policy design which performs optimal over a single future.

Based on the adaptive policymaking approach, Kwakkel et al. (2010) introduce the Adaptive Airport Strategic Planning approach that synthesizes concepts from Flexible Strategic Planning (Burghouwt, 2007) and Dynamic Strategic Planning (De Neufville & Odoni, 2003).

A similar line of research has been conducted by Haasnoot et al. (2013) called Dynamic Adaptive Policy Pathways (DAPP), which helps designing adaptive plans (i.e. pathways that describe a sequence of actions that can be taken depending on how future unfolds). DAPP is the combination of Adaptive Policymaking (APM) with Adaptation Pathways (Haasnoot, Middelkoop, Offermans, Van Beek, & Van Deursen, 2012; Haasnoot M. , 2013).

Many-Objective Robust Decision Making (MORDM) (Kasprzyk, Nataraj, Reed, & Lempert, 2013) has been another approach that offers support for policymaking by synthesizing RDM with many objective evolutionary optimization. MORDM tries to tackle the difficulty of multiple conflicting objectives by developing Pareto approximate trade-off sets. Watson & Kasprzyk (2017) extend the MORDM approach by utilizing robust optimization techniques. Original MORDM applies optimization under a single baseline scenario and then explores candidate scenarios under uncertainty, whereas this extended MORDM performs a multiple multi-objective exploration that helps to find solutions that work well under multiple conditions. Beh et al. (2015) propose another interesting approach which is an adaptive, multi-objective optimal sequencing approach. This approach resembles a combination of adaptation pathways and many-objective robust decision-making, for which various optimal sequence plans are developed for various future scenarios using multi-objective evolutionary algorithms.

Exploratory Modeling and Analysis (EMA) (Agusdinata, 2008) is a computational approach to support the design of long-term plans under deep uncertainty and it can be useful for providing a methodological support for approaches such as APM, RDM or MORDM. EMA generates a large variety of computational experiments by combining plausible models and uncertainties. This ensemble of experiments are used to analyze complex uncertain systems, support the development of long-term strategic policies under deep uncertainty, and test policy robustness. EMA could also be used to develop adaptive policies under deep uncertainty since it allows for generating and exploring a multiplicity of plausible scenarios by sweeping the multi-dimensional uncertainty space. EMA could be used to identify vulnerabilities and opportunities present in this ensemble of scenarios, paving the way for designing targeted actions that address vulnerabilities or seize opportunities. The efficacy of the resulting policies could then be tested over the entire ensemble of scenarios. Moreover, EMA could be used to identify conditions under which changes in a policy are required (Hamarat, Pruyt, & Loonen, 2013). That is, it could help in developing a monitoring system and its associated actions, which is a common approach also used in the Adaptive Policymaking process (APM). APM identifies actions that can *triggered* based on critical values of *signposts* to be tracked as monitoring system. This monitoring system of APM can be integrated in EMA's iterative policy formulation process. It thus appears that EMA could be of use in line with the adaptive policymaking approach.

Not surprisingly, current approaches for policymaking under uncertainty have specific limitations and are not able to handle challenges such as, pre-identifying the conditions under which changes in policy are required or identifying 'optimal' signposts and triggers. For instance, Info-Gap theory focuses only on parametric uncertainties where uncertain parameters are explored in certain intervals with boundaries. Uncertainties that are categorical or related to functions or structures in a model are not tackled by Info-Gap Theory. From an outcome perspective, Real Options analysis focuses mostly on binary outcomes, in other words success or failure of an investment or project. Real options are related to investment decisions, in which the focus is on the success of the investment. However, deep uncertainties prevail when the outcome space has many possibilities that cannot be reduced to success or failure. Furthermore, Real Options analysis assesses the value of options based on their associated probabilities, where they are not available in case of deep uncertainty. In the Robust Decision-making (RDM) approach, the scenario discovery step helps identify vulnerabilities of the candidate policy that shows for which ranges of uncertainties the policy fails to meet its goals. However, RDM does not suggest exploring *opportunities* for which ranges of uncertainties the candidate policy can perform better to exploit such opportunities. Furthermore, there is a lack of guidance on explicitly considering the dynamic adaptation of the plan over time which results in a robust but static strategy (Walker, Haasnoot, & Kwakkel, 2013).

In other words, the RDM approach lacks adaptivity, a crucial element for designing robust long-term policies.

1.4. Gaps to be addressed for supporting model-based policymaking

Dealing with uncertainty in policymaking involves significant challenges that are difficult to handle all at once, namely revealing useful information from the complex uncertainty space, a structured approach for operationalizing adaptivity and supporting policymaking under multiple conflicting objectives.

Mainly due to the lack of advanced analytical support in model-based policymaking it is still very difficult to understand what the joint root causes of problematic behaviours are or under which conditions a system fails to operate. Current approaches in policymaking support do not provide advanced analysis to explore the uncertainty space thoroughly, mostly due to the computational complexity required. Advanced data analysis has not been used for supporting model-based policymaking. The utilization of advanced data analysis techniques becomes more available with the advances on computational power. Various data analysis techniques are available that are used in other fields such as computational biology or data mining. Therefore it is worthwhile to explore the utility of innovative data analysis techniques for exploring the deep uncertainty space.

One of the challenges is to identify the relative importance of the various uncertainties in the input space of the problem of interest. The importance ranking of uncertainties can help design policies that target important uncertainties. To address this problem, feature scoring can be a possible advanced data analysis technique. Feature scoring is a machine learning technique that helps understand the relative impact of the uncertainties on the outcome(s) of interest.

One of the iterative steps of Robust Decision-making is the step to identify scenarios that characterize the vulnerabilities of the proposed policies (Lempert, et al., 2013). Vulnerabilities are plausible events or developments that can deteriorate the policy performance so the objectives are not met. (Kwakkel, Walker, & Marchau, 2010). Scenario discovery uses cluster-finding data-mining algorithms such as the Patient Rule Induction Method (PRIM) that is used to find specific combinations of uncertainty ranges that result in vulnerabilities (Groves & Lempert, 2007). An alternative technique for scenario discovery is Classification and Regression Trees (CART), which is a classification algorithm that can be easily translated into boxes useful for scenario discovery (Lempert, Bryant, & Bankes, 2008). Using such advanced analytical techniques to support model-based policymaking can be useful for addressing the gap of identifying the relations between the complex uncertainty and output spaces.

In a recent special issue of *Technology Forecasting and Social Change* on adaptivity in decision-making, the special issue editors conclude: "Adaptive policymaking is a way of dealing with deep uncertainty that falls between too much precaution and acting too late. While the need for adaptation is increasingly acknowledged, it is still a developing concept, and requires the further development of specific tools and methods for its operationalization" (Walker, Marchau, & Swanson, 2010). More specifically, for adaptive policymaking to become a useful planning approach, it will be necessary to specify in more depth how the various steps can be carried out and which methods and techniques can be employed in each of the steps. Adaptive policymaking needs to move from being a high-level concept captured in a flowchart, to being an operational planning approach. It is possible that many of the available traditional techniques, such as forecasting, scenarios, and exploratory modeling, can be of great use in the various steps of adaptive policymaking. However, exactly how these tools can be employed for the purpose of developing an adaptive policy needs to be studied (Kwakkel, 2010). Formulated more generally, the lack of operationalization of adaptive policymaking for supporting policymaking is another gap that needs to be addressed.

Policymaking for complex and uncertain systems often involves multiple stakeholders where each has a different, possibly conflicting, objective. Different stakeholders may give different weights on the outcomes of interest that lead to different valuations – and this may change in the future in uncertain ways. Clearly, uncertainty in the valuation of outcomes is another key dimension in the definition of deep uncertainty. Therefore, how to deal with the multiplicity of different objectives is also a gap to be addressed in policymaking under deep uncertainty. Multi-objective optimization, which is a field of optimization where there is more than one objective involved, can help model-based policymaking address the issue of multiple conflicting objectives under uncertainty. Multi-objective optimization has been used in fields such as engineering and finance (Marler & Arora, 2004) and can be incorporated in model-based policy support.

1.5. Objective and research questions

The objective of this thesis is to ***improve analytical support for model-based policymaking in order to handle deep uncertainty better***. The approach to be developed aims to help develop adaptive policies that are robust. In this thesis, robustness is defined as "a measure of the insensitivity of the performance of a given strategy to future conditions" (Maier, et al., 2016). Therefore, an improvement of the robustness measure reflects a policy design which performs better under deep uncertainty. The methodological approach will combine EMA and the Adaptive Policymaking framework.

More specifically, based on the analysis in the previous sections of this chapter, the following key questions need to be answered.

- Can advanced analytical tools/techniques/methods be used with Exploratory Modeling and Analysis (EMA) to improve policymaking support under deep uncertainty?
- How can the Adaptive Policymaking framework be operationalized by using EMA to support model-based policymaking?
- In the presence of multiple conflicting objectives under uncertainty, what can be done to improve analytical support for adaptive policymaking?

1.6. Scope and aims of the study

This thesis consists of five chapters where the three main body chapters aim to tackle the key questions listed above and the final chapter will include the discussions.

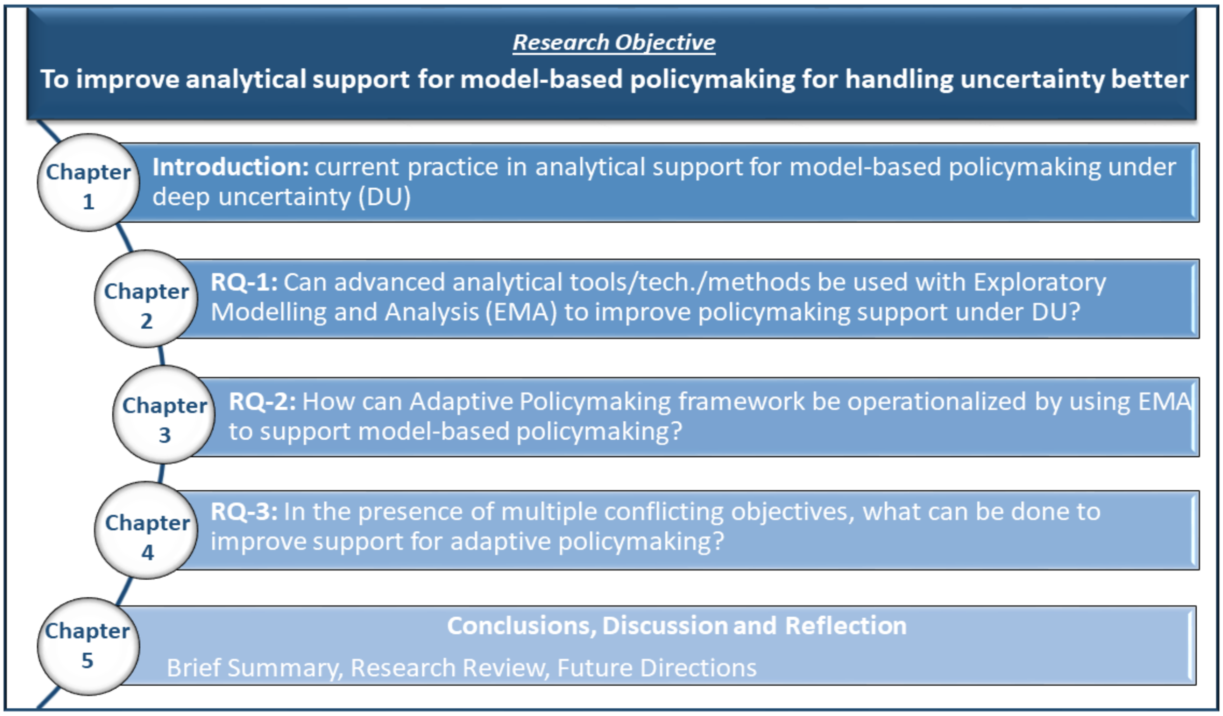

Figure 1: Mapping of research questions to chapters

Chapter 2 will explore the use of analytical tools/methods for supporting policymaking under deep uncertainty. This chapter will investigate the combination of advanced data analytical methods with Exploratory Modeling and Analysis to design dynamic policies. It will be a preparatory step towards a dynamic approach for policy development under deep uncertainty.

In *Chapter 3*, an iterative model-based approach for designing adaptive policies that are robust under deep uncertainty will be introduced. The Adaptive Robust Design (ARD) approach aims to meet the need for operationalization of the Adaptive Policymaking framework. This proposed approach will be illustrated through a case study about energy transitions.

In order to improve support for adaptive policymaking in the presence of conflicting objectives, *Chapter 4* will introduce the use of multi-objective robust optimization in combination with ARD. This chapter will show how advanced data analysis and optimization techniques can be used for robust adaptive policy design in the presence of uncertainty and multiplicity of diverging objectives.

Finally, *Chapter 5* will summarize the answers to the research questions that are posed in this thesis. This chapter will explain how each key question is answered per chapter and how these answers contribute to improve the analytical support for policymaking under deep uncertainty. It will also reflect on the ARD approach, which is the fundamental basis, and the contributions of this study such as using multi-objective robust optimization for policymaking. Lastly, this chapter will put this thesis in the context of current literature and will finish by introducing a future research agenda for further improvements for model-based policymaking under uncertainty.

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In the previous chapter, we have introduced the current approaches that are used for supporting model-based policymaking. However, as stated, current approaches for policymaking have issues about dealing with uncertainty, more specifically deep uncertainty.

The main research question to be answered in the scope this study is how to improve analytical support for policymaking to handle deep uncertainty better. One important issue is the role of adaptivity in policymaking in the presence of deep uncertainty.

To this purpose, we will introduce how Exploratory Modeling and Analysis can be used for exploring the uncertainty space, analyzing the output space extensively for better guidance to develop adaptive policies.

Chapter 2 - Model-based Policymaking under Uncertainty[1]

2.1. Introduction

Decision-making can be a difficult task when there is a lack of knowledge or disagreement about the model that represents the system of interest and about how to evaluate the outcomes. Deep uncertainty can be defined as the situations where analysts do not know, or the parties to a decision cannot agree on (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes (Lempert, Popper, & Bankes, 2003). Since there is a lack of information on the conceptual models, probability of alternatives, it is difficult to *predict* the future. However, there is still the fallacy of thinking that the future can be predicted based on assumptions. These assumptions often fail when dealing with deep uncertainty. Therefore, the focus should be on the exploration of deep uncertainty for an ensemble of plausible futures, instead of best estimate models based on limited assumptions.

Models can be considered as formal representations of the real world. The common aim of the modellers is to represent the real world as a mathematical model and to use that model for supporting decision-making. Modellers make many pre-analytic and analytic assumptions when modeling (parameter estimates, model structures and worldviews). Modellers, who try to forecast the future, often fall in the trap of assuming their assumptions are true. However, in the presence of deep uncertainty, it is impossible to conclude that a single assumption about the future is true. For this reason, the use of models as predictive tools should be challenged. Furthermore, since predictions about the future are usually wrong, it might be misleading to use models for predictive purposes. The goal of this chapter is to illustrate the use of models for decision support in an exploratory manner- exploring an ensemble of plausible futures- instead of focusing on a single (or a few similar) future(s).

Uncertainty analysis for decision-making has been mostly focused on technical and shallow uncertainties about model parameters, input data or initial states. Dealing with model/structural uncertainties is highly complex and difficult. In this chapter, both parametric and structural uncertainties are explored and analyzed.

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[1] This chapter is largely based on the publication Hamarat, C. and E. Pruyt (2011). Energy Transitions: Adaptive Policy Making Under Deep Uncertainty. The 4th International Seville Conference on Future-Oriented Technology Analysis (FTA), Seville, Spain.

2.2. Methodology: Exploratory Modeling and Analysis (EMA)

Exploratory Modeling and Analysis (EMA) (Bankes 2001, Lempert, Popper et al. 2003, Agusdinata 2008) is a research methodology for exploring and analyzing complex and uncertain systems and supporting long term strategic decision-making under deep uncertainty. EMA is a methodology that provides insights and understanding about the system behaviour and effectiveness/robustness of policies by using computational experiments. It originated at the RAND Corporation as Exploratory Modeling (Bankes, 1993) and was relabeled EMA by Agusdinata (2008).

EMA can be contrasted with the use of models to predict system behaviour, where models are built by consolidating known facts into a single package (Hodges and Dewar 1992). In predictive modelling, a single best estimate model is used as a representation for the actual system. Where applicable, this consolidative methodology is a powerful technique for understanding the behaviour of complex systems. Unfortunately, for many systems of interest, the construction of a model that may be validly used as surrogate is simply not a possibility (Campbell, Farmer et al. 1985, Hodges and Dewar 1992). For many systems, a methodology based on consolidating all known information into a single model and using it to make best estimate predictions can be highly misleading. If the model assumptions, such as parameter values or system behaviour, are not valid, then the prediction based on a single model can lead to incorrect decision support. However, models can be constructed that are consistent with the available information, but such models are not unique. Rather than specifying a single model and falsely treating it as a reliable image of the system of interest, the available information supports a set of models, whose implications for potential decisions may be quite diverse. A single model run drawn from this potentially infinite set of plausible models is not a "prediction"; rather, it provides a computational experiment that reveals how the world would behave if the various guesses made in any particular model about the various unresolvable uncertainties were correct. By conducting many such experiments, EMA provides insights and understanding about the system behaviour and effectiveness/robustness of policies under a wide set of different assumptions. EMA is not a modelling technique by itself, but it is a methodology for building and using models under deep uncertainty.

The main steps of EMA can be stated as follows: (1) conceptualization of the system of interest, (2) specification of the uncertainties to be explored, (3) development of *exploratory* fast and relatively simple computational models of the issue of interest, and (4) specification of policy option(s) for the system. In Step (5), an ensemble of future worlds are generated by sweeping uncertainty ranges and varying uncertain structures and boundaries in order to compute the performance of the policies. Computational experiments are performed by exploring uncertainty space. The outcomes of computational experiments are analyzed to reveal insights for designing/improving policy option(s). Steps 4 and 5 are iterated until the suggested policy/policies provide satisfying results.

In model-based policymaking, the input space is composed of various uncertainties and policies to be explored. The output space is the sets of outcomes that is the output of the exploration of the input space. Both the input and output space have too many elements and the nonlinear complexity makes it difficult to understand the relation between the input and output spaces. In order to design better policies, one should have better insight on the dynamics of input and output spaces. Possible solution to seize useful insights is to use pattern analysis and data mining techniques. It should be noted that dealing with time series data by using pattern analysis techniques could be technically difficult. Despite the difficulty level of such techniques, they can be significantly helpful to improve model-based policymaking using EMA. It has been effectively used for model-based policymaking studies (Kwakkel & Pruyt, 2013; Kwakkel & Yucel, 2014) in various fields such as energy studies, environmental sciences, transportation.

There are various methods/techniques/algorithms for data analysis to derive relevant insights. For instance, data-mining techniques, such as classification or regression, or decision-making techniques, such as multi-criteria decision analysis (MCDA) or decision trees, can be good examples of such analytical methods. These are well established and frequently used methods in a wide scope of fields from computer science to biology. EMA can be used flexibly to be in cooperation with such other powerful methods. Other techniques, such as MCDA, can be used in combination with EMA.

2.3. Analytical techniques used together with EMA

In this chapter, we focus on three potential analytical techniques that can be used in line with EMA for improving model-based policymaking support. Feature scoring shows which uncertainties have more importance in terms of the impact on the outcome(s) of interest. Classification and Regression Trees (CART) is a machine-learning method to create subsets of uncertainty space in terms of decision trees (classification and/or regression trees). Patient Rule Induction Method (PRIM) is a data-mining algorithm to find subset(s) in the input space that result in desired output space. PRIM has been used in the context of the *scenario discovery*. It is a computer-assisted approach for finding policy-relevant scenarios by using statistical and data-mining algorithms (Bryant and Lempert, 2010). Scenario discovery approach suggests using not only qualitative but also quantitative algorithms for finding relevant scenarios. These techniques such as CART and PRIM, are used as scenario discovery tools and will help examine the underlying structure of the uncertainty space and understand how the input space is interrelated with output space.

2.3.1. Feature Scoring

Feature scoring is a machine-learning algorithm, which aims to give relative scores to features based on their contribution to the outcome of interest. There are different feature scoring techniques, which are commonly used in fields such as bioinformatics or pattern analysis, that help to identify most important or indifferent features in the model. In this thesis, we use a tree-based method, specifically based on the extra trees algorithm (Breiman, 2001; Geurts et al, 2006). This algorithm creates decision or regression trees where the nodes are split randomly to reduce the variance. It is similar sensitivity analysis in terms of identifying the relevance of uncertainties in the model, but by using a tree-based approach. In the scope of this study, feature scoring can be very useful for identifying the relevant impact of the uncertainties on model outcomes. We use the end state values of the outcomes of interest over time as the output indicator for the feature scoring algorithm. The relative scores of uncertainties can help identifying the importance level of uncertainties. Such information can be used to focus on specific regions in the uncertainty space and to design better guided policies by tackling the output space more effectively.

2.3.2. Classification and Regression Trees (CART)

Another convenient method is Classification and Regression Trees (CART) (Breiman, 1984) which combines classification tree and regression tree together. CART is a popular machine leaning method, which is used for model-based policymaking (Lee et al, 2006; Kurosaki et al., 2010). CART aims to create a binary tree where each branch represents a part of output region with specific characteristics. CART is a powerful method because it can handle both continuous variables by using regression trees and categorical variables by using classification trees simultaneously, whereas similar tree algorithms target either continuous or categorical variables separately. In our analysis, we explore various uncertainties, which can be parametric, continuous, categorical, model structure, etc. Therefore, CART helps us identify regions of interest in the uncertainty space so that policies can be better targeted for specific combinations of uncertainties.

2.3.3. Patient Rule Induction Method (PRIM)

Patient Rule Induction Method (PRIM) (Friedman and Fisher, 1999) is an algorithm, which aims to find combinations of input variables, which result in similar values for the outcomes of interest. PRIM is used to identify subspaces in the input space, which are called PRIM boxes. PRIM, as a scenario discovery tool, has been used in the context of EMA and model-based policymaking to identify the subspaces of experiments of interest. In this chapter, PRIM is used for identifying subspaces of uncertainty space, which can be used for targeting specific regions of interest in the output space.

2.4. Case: A simple case on energy transitions

2.4.1. Details of the model

Energy transitions are deeply uncertain and dynamically complex, where various feedbacks, delays and deep uncertainties about initial values, parameters and structures are prevalent. Given these uncertainties and dynamic complexity, there are many plausible transition trajectories for competing energy technologies, both existing and new sustainable technologies. There is an ongoing debate about sustainability of energy technologies. The necessity of transforming our energy systems towards more sustainable technologies is gaining ground. In this chapter, a System Dynamics model about the competition of four different energy technologies is presented. Technology 1 represents the existing dominant technology and the other three are considered as the future technologies (wind, hydro, solar, etc.) that are more sustainable. The model structures describing the development of all four technologies are represented similarly to give the model generic functionality.

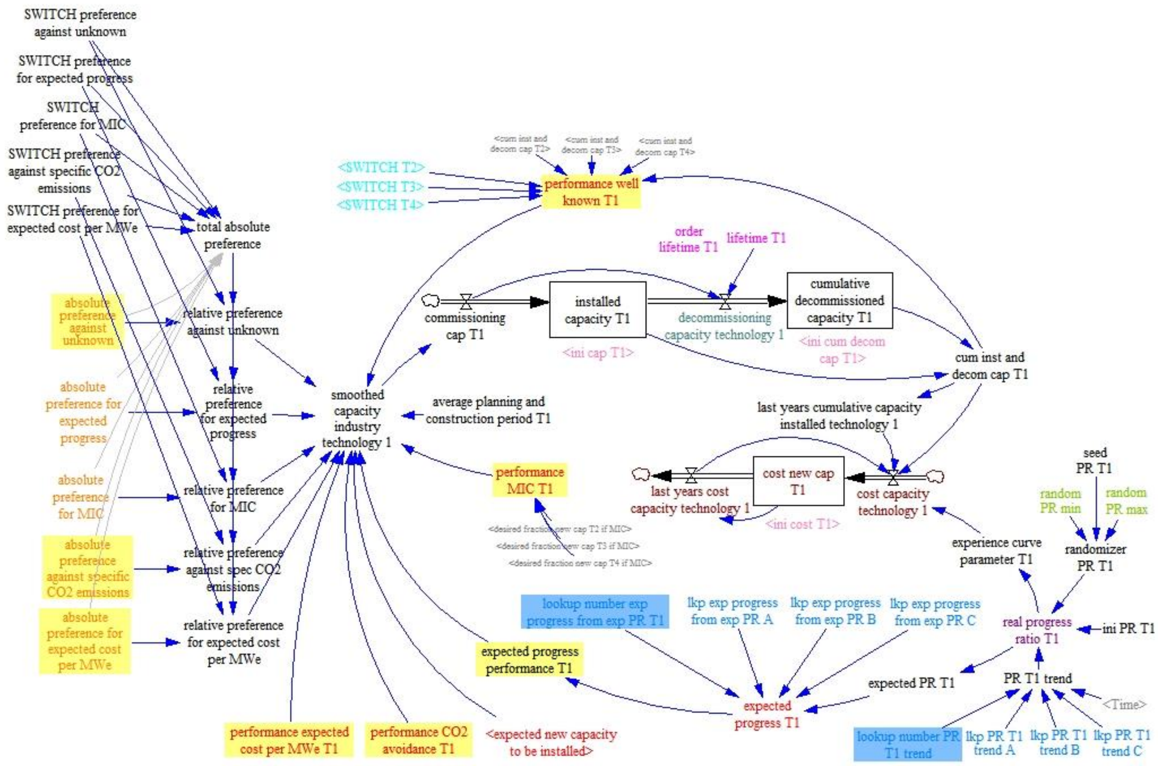


Figure 2: Stock flow diagram of the generic SD model

There are two main stock structures that are *installed capacity* and *cost of new capacity*. Cost of new capacity changes according to an experience curve structure driven by a progress ratio. This progress ratio also influences capacity change via an expected performance structure. Capacity change is driven also by preference structures according to expected progress, marginal cost, CO2 emissions and expected cost per MW energy produced. Since all these structures are deeply uncertain, various methods are employed to represent the uncertainties. For example, randomizers are used for representing real progress ratio and switch structures are utilized for quantifying the relative preferences. In the next section, details of the uncertainties that are explored will be further explained. The main aim of developing such a model is, instead of ignoring or trying to reduce uncertainties, to explore all plausible transition trajectories for energy technologies by including relevant uncertainties. In this study, this model is used to illustrate the methods proposed here and more background about this model can be found on (Pruyt E. , Kwakkel, Yucel, & Hamarat, 2011).

As mentioned before, development of a fast and relatively simple model of the issue of interest is the initial step of EMA and the simple model used in this study is explained in the previous section. Following that, a wide ensemble of plausible futures needs to be generated by sweeping the uncertainty ranges. In our model, uncertainties that are considered include parametric uncertainties (initial values), structural uncertainties (lookup functions, progress ratios), model structure uncertainties (switch structures, preferences) and randomizers. A detailed description of the uncertainties used in the model and the corresponding ranges can be found in Table 1. A range of initial values for capacities, cumulatively decommissioned capacities, and marginal costs of new capacity for each technology is included. Additionally, alternative values for parameters such as lifetimes of technologies and average planning and construction periods are analyzed. Structural uncertainties explored include progress ratios and (structures that enable to swap between) different lookup functions.[2] Switch structures for enabling technologies 3 and 4 and for enabling different preference structures represent deep model uncertainties. Technologies 1 and 2 are always active in the model. Furthermore, randomizers for a more realistic progress ratio structure are utilized and a categorical uncertainty is used for differentiating the order of delays used in the stock-flow structure of the decommissioning of technologies based on their lifetimes.

By sweeping across all these uncertainties, 5000 simulations using a Latin Hypercube Sampling (LHS) technique are performed. The time horizon considered is between years 2000 and 2100. Computational simulations are held by using a shell written in Python programming language forcing Vensim DSS software to execute experiments. Vensim is forced by Python to execute each experiment and output data is stored by Python. Using Vensim and Python together provides several advantages such as easily modeling in Vensim and flexibly making, controlling experimental design, analyzing and visualizing outcomes in Python.

In our analysis, the outcomes of interest are total capacity installed, and total fraction of new technologies (2, 3 and 4). The graphs will be presented in this order in the following sections.

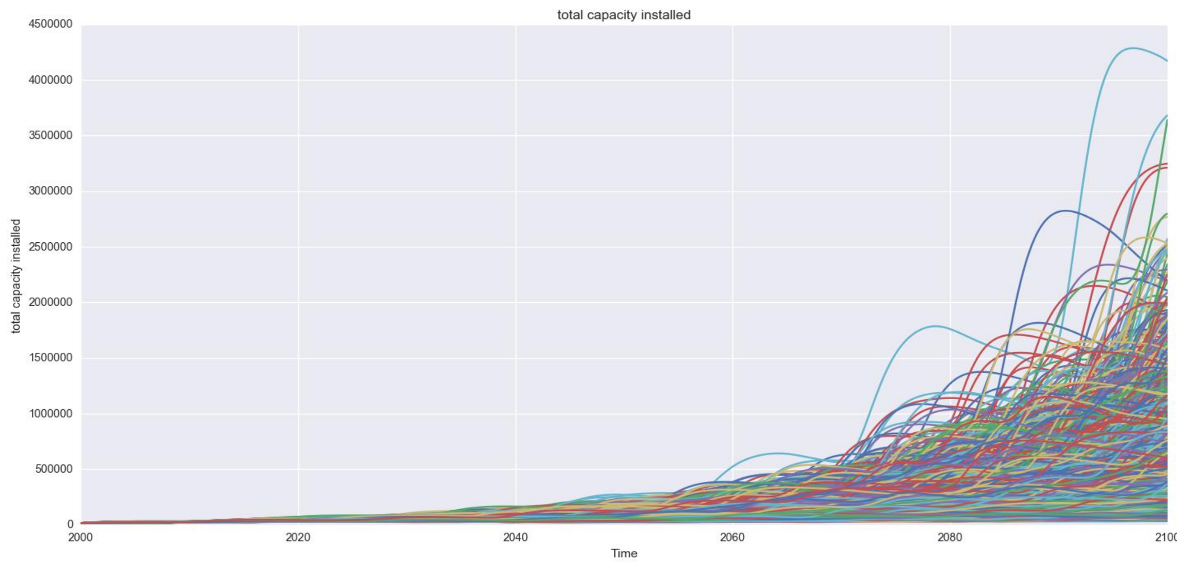
[2] For swapping between three different lookup functions, a categorical uncertainty that can be 1, 2 or 3 enables three different lookups with correspondence to its number.

Table 1: The uncertainties used in EMA and their ranges

Parameter	Ranges
initial capacity Tech1	14000 - 16000
initial capacity Tech2, Tech3, Tech4	1-2
lifetime technology Tech1	30 - 50
lifetime technology Tech2, Tech3, Tech4	15 - 40
initial cumulatively decommissioned capacity Tech1	5M - 10M
initial cumulatively decommissioned capacity Tech2, Tech3, Tech4	1 - 100
average planning and construction period Tech1	1 - 5
average planning and construction period Tech2, Tech3, Tech4	1 - 5
progress ratio Tech1	0.85 - 0.95
progress ratio Tech2, Tech3, Tech4	0.70 - 0.95
initial marginal cost new capacity Tech1	0.5M - 1.5M
initial marginal cost new capacity Tech2, Tech3, Tech4	5M - 10M
performance expected cost per Mwe Tech1	1 - 2
performance expected cost per Mwe Tech2, Tech3, Tech4	1 - 5
performance CO2 avoidance Tech1	4 - 5
performance CO2 avoidance Tech2, Tech3, Tech4	1 - 5
absolute preference for marginal investment cost (MIC)	2 - 5
absolute preference against unknown	1 - 3
absolute preference for expected progress	1 - 3
absolute preference against specific CO2 emissions	2 - 5
absolute preference for expected cost per Mwe	2 - 5
Switches for different preferences	1 / 0
SWITCH Tech3, Tech4	1 / 0
economic growth t1	0.03 - 0.035
economic growth tx (other than t1)	-0.01 - 0.03
random PR min	0.9 - 1.0
random PR max	1.0 - 1.1
seed PR Tech1	1 - 100 (integer)
order lifetime Tech1, Tech2, Tech3, Tech4	1 / 3 / 10 / 1000

2.4.2. Results without Policy

The first analysis is performed without implementing any policy, by only sweeping the uncertainties explained in Table 1 using LHS. Out of 5000 runs, there are 320 cases where all preference switches are zero. It is unrealistic to have no active preference so these 320 cases are excluded out from further analysis. Figure 3 shows 4680 single lines for each run for the total capacity installed and the total fraction of new technologies. The range of the end value for the total fraction of new technologies is spread between 0 and 1 widely. However, it is difficult to derive useful insight from this representation of the outcome of 4680 LHS runs because it does not reveal clear distinct patterns. Installed capacities of technologies tend to increase after 2060 and for some of the technologies, cyclic behaviors are observed. In order to derive useful insight from such output data, innovative approaches are required. An available technique for a better insight is to illustrate the envelopes of upper and lower limits for each graph and a histogram distribution of the end states of outcomes (See Figure 4).



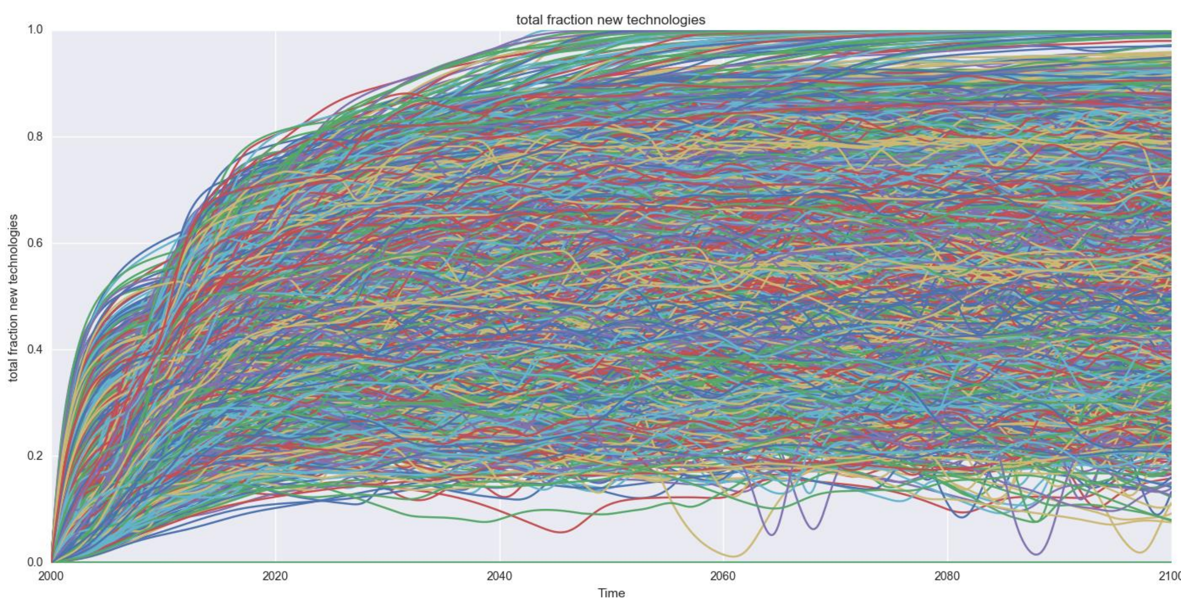


Figure 3: LHS results for 4680 runs without policy implementation[3, 4]

Figure 4 illustrates the envelopes of outcomes and histograms of the end states of each graph. Although the total capacity installed seems to be distributed along a wide range, the histogram in

[3] The figures including 2 different graphs are presented in the order of (from top to bottom): total capacity installed and total fraction of new technologies.

[4] Currently, more advanced and improved visualization techniques are available. The visualization techniques used in this thesis are based on the available techniques at the time when the research was conducted.

Figure 4 reveals that most of the end states of the runs are gathered around low levels that is below 60%. For the total fraction of new technologies, it shows a bell shaped behavior. In order to ensure a better future for new technologies, the bell shape should be forced upwards which means to increase the number of cases with higher end states.

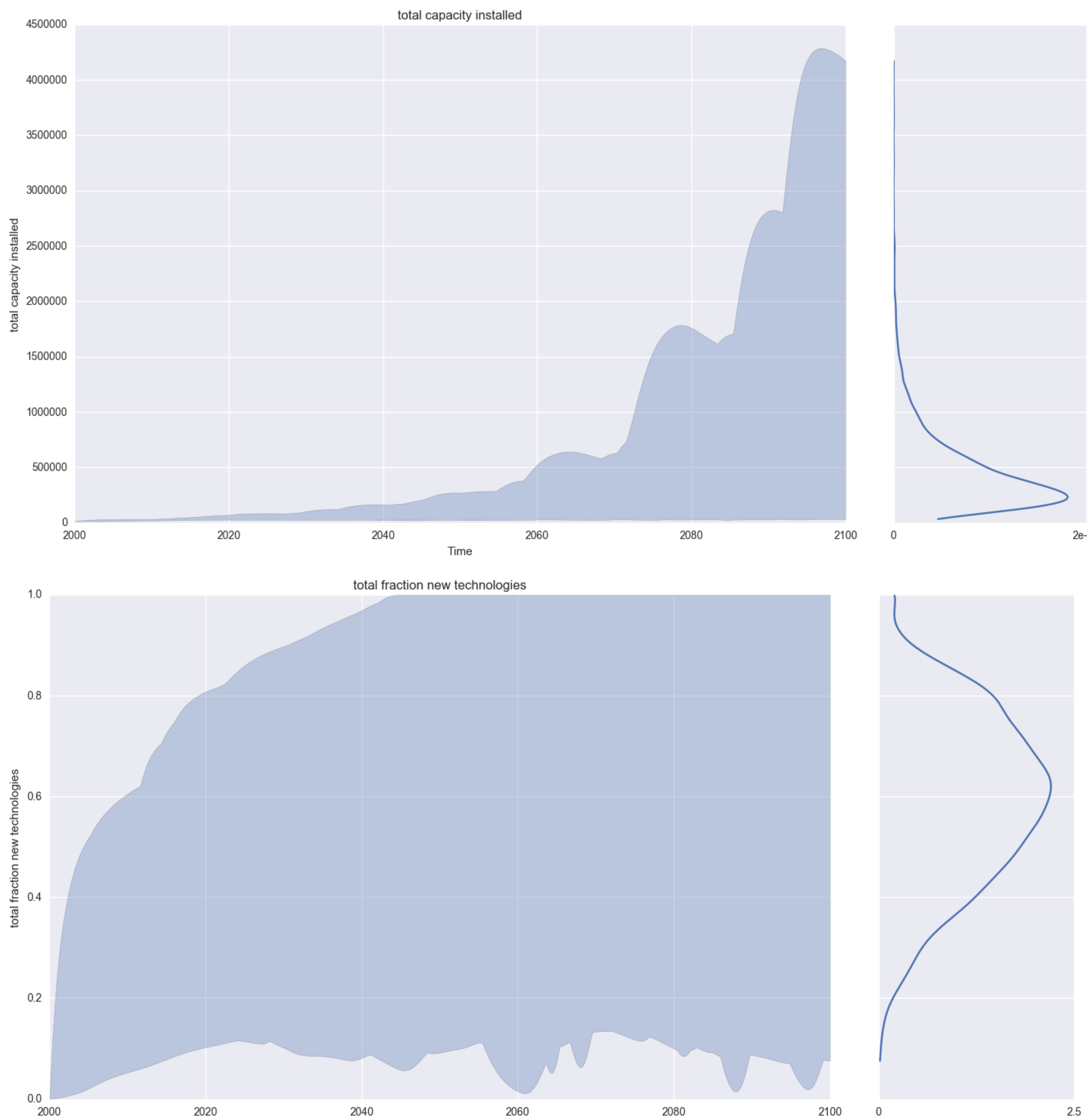


Figure 4: Envelopes and end state histograms for 4680 runs without policy

2.4.3. Advanced analysis (Feature Scoring, CART, PRIM)

Feature scoring helps identify the importance score of various uncertainties relative to the outcome of interest. In this thesis, we use a tree-based feature scoring algorithm, which uses extra trees (Geurts et al, 2006). We analyzed the initial dataset of 4680 runs without policy by using feature scoring algorithm. Table 2 shows the first 20 most important uncertainties where the importance is relative to their impact on the end state of the total fraction of new technologies.

Table 2: First 20 most important uncertainties in relation with the total fraction of new technologies

Uncertainty	Importance Score
SWITCH preference against specific CO2 emissions	0.2177
SWITCH preference for expected cost per MWe	0.1456
SWITCH Tech4	0.1048
SWITCH Tech3	0.1037
SWITCH preference against unknown	0.0975
performance expected cost per MWe Tech2	0.0273
SWITCH preference for MIC	0.0258
ini PR Tech2	0.0242
performance CO2 avoidance Tech2	0.0225
SWITCH preference for expected progress	0.0123
lifetime Tech2	0.0118
absolute preference against unknown	0.0098
lifetime Tech1	0.0090
performance CO2 avoidance Tech4	0.0083
performance CO2 avoidance Tech3	0.0081
performance expected cost per MWe Tech1	0.0075
ini cost Tech1	0.0065
performance expected cost per MWe Tech4	0.0065
order lifetime Tech1	0.0061
performance expected cost per MWe Tech3	0.0060

The feature scores show that the variations in preferences are more important than the other uncertainties. Since these are model structure uncertainties, it is not surprising that they have direct impact on the fraction of new technologies. Performance related uncertainties of Technology 2 and the lifetimes of Technology 1 and 2 have also important impact on the fraction of new technologies. Feature selection helps identify the importance of the uncertainties in the model but it does not tell much about what range of the uncertainty results in (un)favorable outcomes.

Classification and Regression Trees (CART) is a decision tree algorithm, which can be used with both categorical and continuous variables together. Our uncertainty range includes both categorical and continuous uncertainties; CART can help us identify which uncertainties[5] play an important role in the region of interest for the selected outcome. As seen in Figure 4, there is a significant

[5] Switch structures are excluded from CART because they are so dominant on the results that only the switch uncertainties appeared on the CART boxes.

number of runs where the end state of the total fraction of new technologies is below 40%. The total number of cases of interest that fall in this undesired region is 614, which is approximately 13% of 4680 runs. CART identifies the combination of uncertainty ranges where the outcome of interest is the result of the selected uncertainty ranges. A combination of uncertainty ranges is called a box, which can be interpreted as multidimensional region in the uncertainty space. Table 3 shows the summary details of the three uncertainty boxes that are identified using CART. The total number of the cases that can be identified by these three boxes is 374, which is more than half of the 614 cases of interest. Coverage is defined as the number of cases identified by a box over the total number of cases of interest (e.g. for CART box A, 138/614 = 22.5%). The CART boxes where the number of cases of interest is less than 100 are not shown due to low coverage levels.

Table 3: Summary details for three CART boxes

	Coverage	# of Uncertainties	# of Cases of Interest
CART box A	22.5%	3	138
CART box B	21.8%	2	134
CART box C	16.6%	3	102

The first box covers 138 cases and it is identified by combination of three uncertainties. Similarly, the second and third boxes covers 134 and 102 cases, and identified by two and three uncertainties, correspondingly. Table 4 shows the range combination of the relevant uncertainties for each box, where they are highlighted as red. To interpret this table, when the red highlighted uncertainties are between the ranges shown, the end state of the total fraction of new technologies is below 40%.

Table 4: Uncertainty ranges for the three CART boxes

Uncertainties	**CART box A**		**CART box B**		**CART box C**	
	Min	**Max**	**Min**	**Max**	**Min**	**Max**
absolute preference against unknown	2.26	3.00	1.00	3.00	1.00	2.26
performance CO2 avoidance Tech3	1.00	2.79	1.00	4.00	1.00	4.00
performance CO2 avoidance Tech4	1.84	4.00	1.00	1.84	1.84	4.00
lifetime Tech1	30.00	50.00	38.26	50.00	30.00	50.00
lifetime Tech4	15.00	40.00	15.00	40.00	15.00	25.87

It is clear that the lower levels of CO2 avoidance performances for new technologies have negative impact on achieving higher end states of the fraction of new technologies. As shown in CART box A, the performance CO2 avoidance of Tech3 is on the lower range and for Tech4 on the middle range of the full range of 1 to 5. In combination with upper range of absolute preference against unknown, the total fraction of new technologies stay below 40%. Additionally, the higher levels of the lifetime of the Technology 1 should also be considered as playing an important role.

Another method for further analysis is PRIM, which can help identify the characteristics of the specific regions in outcome space. We applied the PRIM algorithm on the 4680 runs and specifically focused on the outcomes where the end state of the fraction of new technologies is below 40%. Three boxes are selected from the PRIM analysis and the details of the boxes are shown in Table 5.

Table 5: Summary details for three PRIM boxes

	Coverage	# of Uncertainties	# of Cases Covered
PRIM box A	55.2%	3	339
PRIM box B	49.8%	4	306
PRIM box C	48.5%	5	298

The specific ranges of the uncertainties that are included in the boxes are shown in Table 6. It is clear that the cases where new technologies are not activated lead to outcomes where the fraction is below 40%. It is clear that new technologies should be promoted to give more opportunity for renewables so that higher levels of the renewable fraction can be achieved. PRIM box B and C show that when Technology 3 and 4 are not activated and CO2 avoidance performance of Technology 2 is low in combination with CO2 emission preference activated, new technologies become less preferable over the Technology 1. As the switches for Technology 3 and 4 are zero, this means that Technology 2 is less preferable over Technology 1. It can be interpreted that it is crucial to make new technologies preferable over the existing technology.

Table 6: Uncertainty ranges for the three PRIM boxes

Uncertainties	PRIM Box A		PRIM Box B		PRIM Box C	
	Min	**Max**	**Min**	**Max**	**Min**	**Max**
SWITCH Tech3	0	0	0	0	0	0
SWITCH Tech4	0	0	0	0	0	0
SWITCH preference against specific CO2 emissions	1	1	1	1	1	1
performance CO2 avoidance Tech2			1.00	3.36	1.00	3.36
average planning and construction period Tech1					1.00	4.75

2.4.4. Results with Static Policy

In the light of the previous analysis by using feature scoring, CART and PRIM, the preference related uncertainties and the lifetimes of the technologies have impact on the progress of the new technologies. Therefore, the first part of the initial policy design focuses on making the new technologies more preferable by introducing cost attractiveness. An upper limit of 1.000.000 Euros is set for the initial marginal cost for new capacities of Technology 2, 3 and 4. This is a static approach where only an upper limit is set for the costs of new technologies. The aim of this policy design is to mimic the structure of the governmental and/or national incentives for promoting renewable technologies. The other part of the initial policy design targets the lifetimes of the new technologies. The lifetimes of all four technologies are explored using the uncertainty ranges specified in Table 1. This policy design proposes that the lifetime of the new technologies will improve as technology advances. So, the lifetimes of the technologies 2, 3 and 4 are assumed to increase by 5 years every 25 years until 2050. The reason for stopping the increase after 2050 is that the lifetime improvement is expected to reach its maturity.

The proposed cost and lifetime structures are implemented as a policy design and the 4680 simulations (excluding 320 unrealistic cases where all preference switches are zero) are rerun on the same uncertainty range. Figure 5 shows the envelopes and end state histograms for No Policy and Static Policy together for comparison. Although the envelopes do not reveal much insight, the end state histograms show that there is an improvement on achieving higher levels of end states by implementing the static policy. The mean of the bell shaped histogram for static policy increases approximately from 50%, as for no policy, towards 70%. Although the static policy helps a slight improvement, there is still need for better policy design, which will ensure higher levels of the fraction of the new technologies. A dynamic policy that can adapt over time under deep uncertainty may improve the fraction of new technologies.

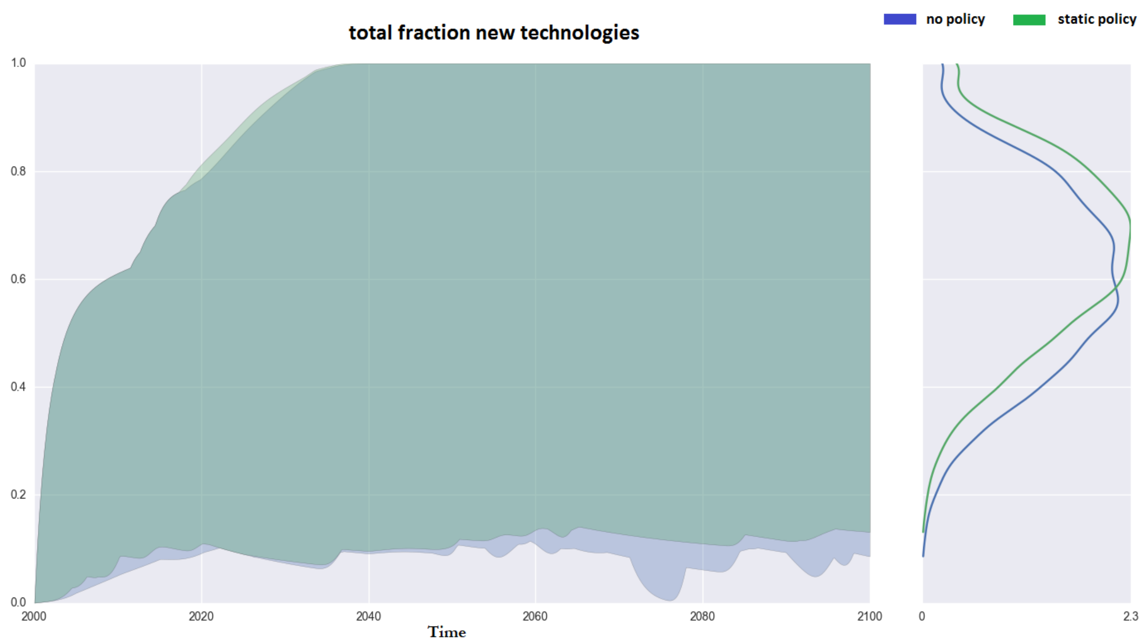


Figure 5: Envelopes and end state histograms comparing No Policy and Static Policy

2.4.5. Results with Dynamic Policy

The models in this study and, generally, with EMA are used for analyzing the behavior of a system over time. Therefore, the dynamics over time is important for understanding the system behavior and designing policies that can adapt over time. In order to propose dynamic policy designs, it is necessary to understand the outcomes of the static policy. Similar to the previous analysis, PRIM is used to get a better insight about the uncertainties and their relation with the outcome of interest. We applied the PRIM on the outcomes of the static policy where the fraction of new technologies are below 40%. The algorithm returned the PRIM box A with a coverage percentage of 68.4%. The details can be seen in Table 7.

Table 7: Details for the PRIM box where the fraction of new technologies is below 40%

	Coverage	# of Uncertainties	# of Cases Covered
PRIM box A	68.4%	3	212

There are three uncertainties included in this box, where all uncertainties are switch structures. The details of the PRIM results are presented in Table 8 that means that if new technologies are not activated, it will result in low levels of new technology fraction.

Table 8: PRIM results for the fraction of new technologies is below 40%

Uncertainties	< 40%	
	Min	Max
SWITCH Tech3	0	0
SWITCH Tech4	0	0
SWITCH preference against specific CO2 emissions	1	1

So far, we used PRIM to analyze the undesirable regions in the outcome space. However, it is also possible to apply PRIM for understanding the uncertainty relations for the positive outcome space. Therefore, we used PRIM this time for analyzing the outcome space where the fraction of new technologies above 80%. The aim is to find out what combination of uncertainties result in desirable results. The total number of cases where the end state of the new technology fraction is above 80% is 916. PRIM identified one box that covers 78.1% of 916 cases, namely 715 cases of interest (see Table 9). This means that 715 of 916 desirable cases can be explained with a specific uncertainty combination whereas the remaining cases do not relate to a specific uncertainty combination.

Table 9: Summary for the PRIM box where the fraction of new technologies is above 80%

	Coverage	# of Uncertainties	# of Cases Covered
PRIM box B	78.1%	2	715

The uncertainties identified by PRIM are shown in Table 10. When the two switches for preferences on unknown and CO2 emissions are zero, then the fraction of new technologies has end states that are higher than 80%. There are 5 different preferences that are marginal investment cost (MIC), expected progress, expected cost per MWE, against unknown and specific CO2 emissions. The PRIM box B where the switches for unknown and specific CO2 emissions are not active can be interpreted that the other preferences have more impact for higher than 80% fraction of new technologies.

Table 10: PRIM results for the fraction of new technologies is above 80%

Uncertainties	> 80%	
	Min	Max
SWITCH preference against unknown	0	0
SWITCH preference against specific CO2 emission	0	0

In addition to the static policy design, it is crucial to include dynamic policy design to ensure higher levels of new technology fraction. In the light of both the negative and the positive PRIM analysis, preferences for (1) CO2 emissions, (2) expected cost per MW energy produced and (3) marginal investment cost (MIC) have been selected to be components of the dynamic policy design. Instead of static constants, these preferences have been set to change dynamically according to the installed capacity level of technology 1 (See Figure 6). The higher the installed capacity of Technology 1, the more selected preferences preferred so that the new commissioning of Technology 1 slows down. The aim of this dynamic policy design is to slow down the commissioning of Technology 1 if the installed capacity of Technology 1 increases. This policy can help achieving higher level of new technologies fraction.

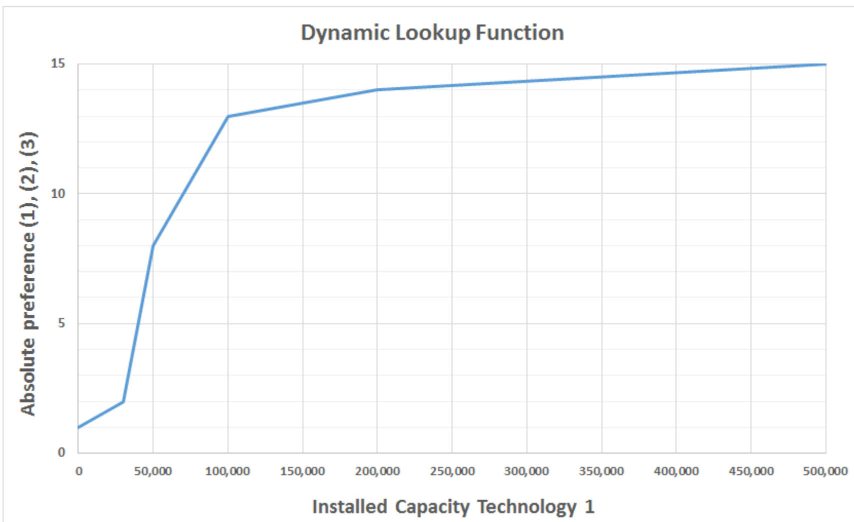


Figure 6: Lookup table used for absolute preferences for (1) specific CO2 emissions, (2) expected cost per MW energy produced and (3) MIC

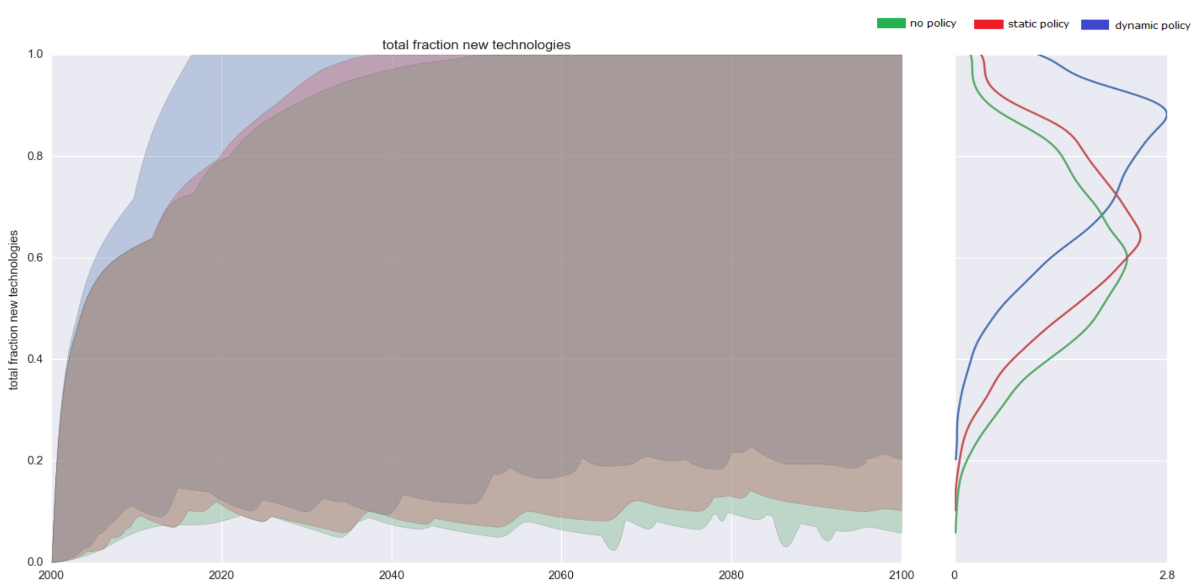


Figure 7: Envelopes and end state histograms comparing No Policy, Static Policy and Dynamic Policy

By implementing the proposed designs in the model, a dynamic policy is designed and similarly 4680 runs (320 cases excluded due to infeasibility) are executed by exploring the same uncertainty space as static policy and no policy options. All three options are represented together in the same graph (See Figure 7) for comparing the policy options. As seen previously, there is only slight improvement from No Policy (green line) to Static Policy (red line). On the contrary, Dynamic Policy (blue line) makes a significant difference for ensuring higher levels of new technologies. The peak of the bell shaped curve of the blue line increased approximately to 90%, in comparison to 70% for the red line of static policy. Figure 7 clearly shows the contribution of the dynamic policy design for achieving desirable outcomes.

2.5. Conclusions

In this study, a System Dynamics model of energy transitions has been explored by sweeping the uncertainties listed in Table 1. The analysis of different policies reveals that a dynamic policy performs better than a static policy for sustaining a better future for new sustainable energy technologies. In order to better illustrate the policy comparison, the number of runs that are above certain levels (20%, 30%, 40%, 50%) of the fraction of new technologies out of 4680 runs are shown in Table 11 for each policy option. There is a clear dominance of the dynamic policy over the other policy options for almost all the levels. For instance, almost 95% of all 4680 runs with dynamic policy have an end state of at least 50% fraction of new technologies. For the dynamic policy, there are still approximately 2% of runs that are below 40%. In addition, there is still almost 4% of runs that have an end state between 40% and 50% and this region of outcomes should be investigated in depth.

Table 11: Number of runs over certain levels of new technologies fraction for 4680 runs

	> 20%	> 30%	> 40%	> 50%
No Policy	4649	4483	4084	3318
Static Policy	4668	4608	4362	3852
Dynamic policy	***4680***	***4666***	***4604***	***4434***

As the main purpose of this chapter is to illustrate the use of analytical tools/methods for supporting policymaking, we have used EMA as the primary methodology. EMA is a methodology for handling deep uncertainty in dynamically complex issues of interest by using models. In this chapter, a System Dynamics model about energy transitions is explored and analyzed. Various deep uncertainties about parameters, functions and model structures are swept across wide ranges. A dynamic policy that can adapt over time is implemented to ensure a better future for new energy technologies. The advantage of dynamic policymaking is its flexibility against uncertainties and the ability to adapt over time. Dynamic policymaking ensures that it is possible to implement policies that are robust over an ensemble of plausible futures (Walker, Rahman, & Cave, 2001; Haasnoot, Kwakkel, Walker, & ter Maat, 2013). Since the future of energy transitions is dynamically complex and deeply uncertain, policy recommendation is difficult under these conditions. Although a relatively simple dynamic policy has been implemented in this chapter, it illustrates that dynamic policymaking helps better for ensuring desirable outcomes under conditions of deep uncertainty.

There are various algorithms/tools available, which can be useful for time series data analysis and help for a better deep uncertainty analysis. In this study, we have used algorithms and techniques such as PRIM, CART and feature scoring for analyzing the outcome space and understanding the relations between uncertainties and model outcomes. These techniques help designing better guided and targeted policies to achieve desired outcomes. For instance, feature scoring allows us to understand the importance ranking of the uncertainties on the outcome space. However, this technique identifies the individual importance of uncertainties but does not show the importance ranking for combinations of uncertainties. As the elements of nonlinear and complex systems interact, the uncertainties need to be considered in relation with each other. Nevertheless, feature scoring guides us to which uncertainties to focus on. PRIM and CART aim to cover uncertainties together and to identify relevant combinations of uncertainties where the outcome space has the desired characteristics. Both are used as scenario discovery algorithms to find regions of interest in the uncertainty space for designing policies that target such regions. However, there is no clear evidence that one is superior to the other (Kwakkel & Jaxa-Rozen, 2016; Lempert, Bryant, & Bankes, Comparing algorithms for scenario discovery, 2008). PRIM requires more user interaction such as setting various algorithm parameters but the results are easier to interpret by users. On the contrary, CART requires less interaction for execution but can result in many uncertainty sub-spaces that will make it difficult for scenario discovery.

Using such data analysis algorithms/techniques in combination with Exploratory Modeling and Analysis (EMA) for analyzing complex and uncertain systems has been an innovative approach. During the course of this study, using EMA with data analysis techniques was not yet established in a structured way but was being done more in an exploratory and unpremeditated manner. Moreover, we have not compared the algorithms for which one is better. It is crucial that a more structured framework, which combines EMA together with innovative data analysis algorithms, should be introduced. Such framework will make analysis more evident and coherent that will lead to improved policy support. Thus, EMA will be a more powerful and elaborate method for developing better policy designs under deep uncertainty.

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We have demonstrated how Exploratory Modeling and Analysis (EMA) can be effectively used for developing adaptive policies under deep uncertainty in the previous chapter. Together with EMA, we have used various methods such as Feature Scoring, CART or PRIM. However, using EMA together with such techniques had been done not by using a clear established approach.

In the next chapter, we will introduce the Adaptive Robust Design (ARD) approach, which is an iterative model-based approach for designing adaptive policies that are robust under deep uncertainty. It is based on an established framework, Adaptive Policymaking framework. This chapter shows that ARD can be used to develop long-term, adaptive and robust policies.

Chapter 3 - The Adaptive Robust Design (ARD) Approach[6]

3.1. Introduction

Conceptual, formal, and computational models are commonly used to support decision-making and policymaking (Walker, Harremoës et al. 2003, Kwakkel, Walker et al. 2010, Pruyt and Hamarat 2010, Yucel 2010, Pruyt, Kwakkel et al. 2011). The term 'model' refers here to a representation of the most crucial aspects of a system of interest for extracting usable information (Eykhoff 1974). The term 'decision-making' is used here for the act or process of making strategies or conscious decisions by an individual or group of actors, and 'policymaking' for the act or process of designing policies by those in charge of designing (public) policy. Hence, decision-making is more general than, and to some extent includes, policymaking. Although the approach proposed in this chapter applies equally well to long-term decision-making as to policymaking, we will, from here on, consistently refer to 'policymaking' and 'policies', for our work mainly focuses on policymaking and the case we use to illustrate the approach here relates to policymaking for stimulating energy transitions.

Although some uncertainty, defined here as any type of aberration from utter certainty (Walker, Harremoës et al. 2003), is mostly taken into account in traditional model-based policymaking, it mainly includes what is known and certain. However, uncertainty is prevalent in complex systems and policymaking related to complex issues. Policy failures are often attributable to the omission of uncertainties in policymaking (Walker, Marchau et al. 2010). Policies that would be optimal for one particular scenario often fail in most other scenarios. In addition, policies that are optimal for dynamically complex issues at a particular point in time often fail at other moments in time. Hence, in case of complex issues under uncertainty, there is a strong need for policies that are designed to adapt over time to new circumstances and surprises, i.e. adaptive policies, and to perform acceptably well in all circumstances, i.e. robust adaptive policies (Lempert, Popper et al. 2003, Walker, Marchau et al. 2010).

In order to develop policies under uncertainty, analysts often use techniques such as exploratory scenarios (van der Heijden 1996), Delphi surveys (Lindstone and Turoff 1975), and the analysis of wild cards and weak signals (Saritas and Smith 2011). Characteristic for these techniques is that they aim at charting the boundaries of what might occur in the future. Although useful, these traditional methods are not free of problems. Goodwin and Wright (2010 , p. 355) argue that "all the extant forecasting methods – including the use of expert judgment, statistical forecasting,

[6] This chapter is largely based on the publication Hamarat, C., J. H. Kwakkel and E. Pruyt (2013). "Adaptive Robust Design under Deep Uncertainty." Technological Forecasting and Social Change **80**(3): 408-418.

Delphi and prediction markets – contain fundamental weaknesses". Popper et al. (2009) state that the traditional methods "all founder on the same shoals: an inability to grapple with the long-term's multiplicity of plausible futures".

Modeling used for policymaking under uncertainty long faced the same inability to grapple with the long-term's multiplicity of plausible futures. Although testing parametric uncertainty is standard practice in modeling, and the importance to present a spectrum of runs under very different hypotheses covering the range of their variation was recognized decades ago (Meadows, Richardson et al. 1982, p.149), modellers were until recently unable to truly overcome this inability due to computational barriers encountered when dealing with complex systems (Lempert, Popper et al. 2003). Adaptive foresight studies would also hugely benefit from enhanced computational assistance (Eriksson and Weber 2008).

If uncertainties are not just parametric, but also relate to functional relations, model hypotheses and aspects, model structures, mental and formal models, worldviews, modeling paradigms, the effects of policies on modeled systems, and the lack of consensus on the valuation of model outcomes, i.e. in case of 'deep uncertainty', then traditional modeling and model-based policymaking tends to fail. Deep uncertainty pertains according to Lempert et al. (Lempert, Popper et al. 2003) to those "situations in which analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models which describe the relationships among the key driving forces that shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes". Deep uncertainty pertains, in other words, from a modellers' perspective to situations in which a multiplicity of alternative models could be developed for how (aspects of) systems may work, many plausible outcomes could be generated with these models, and outcomes could be valued in different ways, but one is not able to rank order the alternative system models, plausible outcomes, and outcome evaluations in terms of likelihood (Kwakkel, Walker et al. 2010). Hence, all alternative system models, plausible scenarios, and evaluations require consideration, without exception, and none should be treated as the single best model representation, true scenario, or correct evaluation. It is clear that there is a strong need for policymaking approaches that allow for dealing with deep uncertainty, i.e. with many different kinds of uncertainties, multiple models, a multiplicity of plausible scenarios and evaluations of these scenarios (Porter, W.B. et al. 2004).

In this chapter, we propose an iterative model-based approach for designing adaptive policies that are robust under deep uncertainty. The approach starts from a conceptualization of the decision problem and the identification of the key uncertainties. Next, an ensemble of models is developed that explicitly allows for the exploration of the uncertainties. The behavior of the ensemble is analyzed and troublesome or advantageous (combinations of) uncertainties are identified, stimulating policy design. Iteratively, the initial design is fine-tuned until there are no remaining troublesome (combinations of) uncertainties or the policy is deemed satisfactory based on other grounds. This approach thus explicitly uses the multiplicity of plausible futures for policy design, addressing one of the shortcomings of many traditional approaches and practices, i.e. the poor utilization of the potential to be prepared for uncertainties and surprises of future developments (Volkery and Ribeiro 2009). The systemic characteristic of the proposed approach enables a holistic and systemic exploration of the future, which is of great importance in FTA (Cagnin and Keenan 2008).

The proposed approach is illustrated by means of a long-term policymaking case related to the transition of energy system toward sustainability. Energy systems are complex, their development over time is dynamically complex, and many aspects related to these systems and their future developments are deeply uncertain. Current attempts at steering the transition toward a more sustainable and cleaner configuration are static and may not be very effective and efficient in various futures, i.e. they may not be robust. This energy transition case is therefore used for illustrating how this approach could be used for policymaking, and more generally, decision-making under deep uncertainty.

The rest of the chapter is organized as follows. Section 3.2 introduces an adaptive policymaking framework and our Adaptive Robust Design approach. Section 3.3 contains the energy transition case and the illustration of our approach to it. Section 3.4 includes the discussion. Concluding remarks are made in section 3.5.

3.2. Methodology: The Adaptive Robust Design (ARD) Approach

3.2.1. The Adaptive Policymaking Framework

Under deep uncertainty, predictive approaches are likely to result in policies that perform poorly. In response, an alternative policymaking paradigm has emerged. This paradigm holds that, under deep uncertainty, policymaking needs to be dynamic with built-in flexibility (Walker, Rahman et al. 2001, Lempert, Popper et al. 2003, Neufville and Odoni 2003, Albrechts 2004, Schwartz and Trigeorgis 2004, Eriksson and Weber 2008, Swanson, Barg et al. 2010). The initial ideas for this paradigm were developed almost a century ago. Dewey (1927) put forth an argument proposing that policies be treated as experiments, with the aim of promoting continual learning and adaptation in response to experience over time (Busenberg 2001). Policy learning is also a major issue in evolutionary economics of innovation (Mytelka and Smith 2002, De La Mothe 2006, Faber and Frenken 2009). Early applications of adaptive policies are also found in the field of environmental management (Holling 1978, McLain and Lee 1996), where policies are designed from the outset to test clearly formulated hypotheses about the behavior of an ecosystem being changed by human use (Lee 1993). A similar attitude is also advocated by Collingridge (1980) with respect to the development of new technologies. Given ignorance about the possible side effects of technologies under development, he argues that one should strive for correctability of decisions, extensive monitoring of effects, and flexibility. More recently, Brans et al. (Brans, Macharis et al. 1998) and Walker et al. (2001) developed a structured, stepwise approach for dynamic adaptation. Walker et al. (2001) advocate that policies should be adaptive: one should take only those actions that are non-regret and time-urgent and postpone other actions to a later stage. In order to realize this, it is suggested that a monitoring system and a pre-specification of responses when specific trigger values are reached should complement a basic policy. The resulting policy is flexible and adaptive to the future as it unfolds.

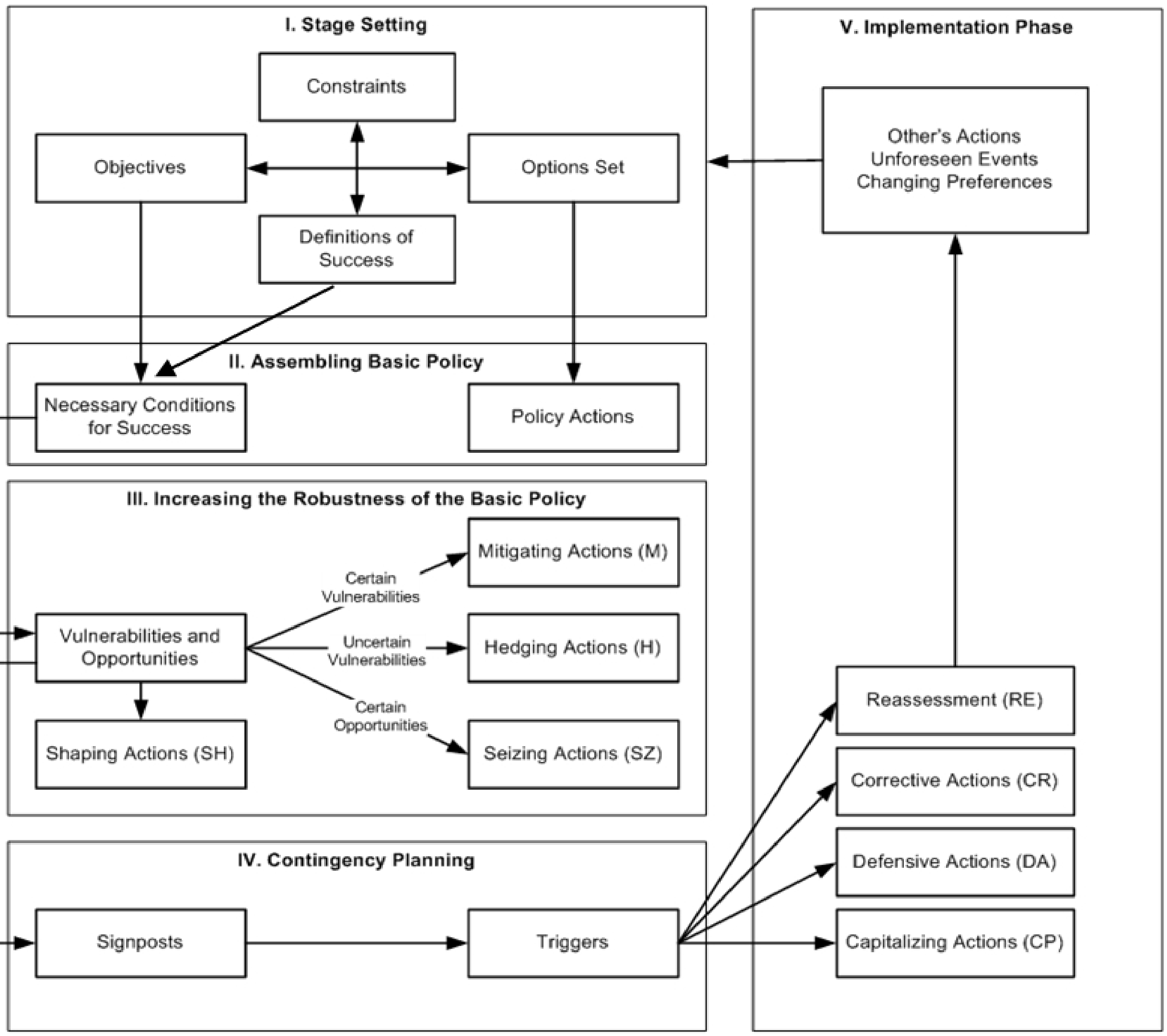

Figure 8: Steps of the Adaptive Policymaking Framework. Source: (Kwakkel, Walker et al. 2010)

Figure 8 shows a framework that operationalizes the high-level outline of adaptive policymaking. In Step I, the existing conditions of an infrastructure system are analyzed and the goals for future development are specified. In Step II, the way in which this is to be achieved is defined. This basic policy is made more robust through four types of actions, which are specified in Step III, namely by mitigating actions to reduce the certain adverse effects of a policy; hedging actions to spread or reduce the negative impacts of uncertain adverse effects of a policy; seizing actions to profit from opportunities; and shaping actions to reduce the likelihood that an external condition or event that could make the policy fail will occur, or to increase the chance that an external condition or event that could make the policy succeed will occur. Even with the actions taken in Step III, there is still the need to monitor the performance of the policy and take action if necessary. This is called contingency planning, and is implemented in Step IV. Signposts specify information that should be tracked in order to determine whether the policy is progressing toward success. Critical values of signpost variables (triggers) are chosen, beyond which actions should be implemented to ensure that the policy keeps moving the system at a proper speed in the right direction. There are four different types of actions that can be triggered by a signpost: defensive actions are taken to reinforce the basic policy, preserve its benefits, or meet outside challenges in response to specific triggers that leave the basic policy unchanged; corrective actions are adjustments to the basic policy; capitalizing actions aim at taking advantage of opportunities that improve the outcomes of the basic policy; and a reassessment of the policy is initiated when the analysis and assumptions critical to the policy's success have lost validity.

In a recent special issue of *Technological Forecasting and Social Change* on adaptivity in decision-making, the guest editors conclude, "Adaptive policymaking is a way of dealing with deep uncertainty that falls between too much precaution and acting too late. While the need for adaptation is increasingly acknowledged, it is still a developing concept, and requires the further development of specific tools and methods for its operationalization" (Walker, Marchau et al. 2010). More specifically, for adaptive policymaking to become a useful policymaking approach, it is necessary to specify in more depth how the various steps could be carried out and which methods and techniques could be employed in each of the steps. That is, adaptive policymaking needs to move from being a high-level concept captured in a flowchart, to being a detailed policymaking approach. A possible qualitative approach for operationalizing the Adaptive Policymaking Framework is through structured workshops (Van der Pas et al. , 2012). A possible quantitative approach for operationalizing the Adaptive Policymaking Framework is by using Exploratory Modeling and Analysis (Bankes 1993, Agusdinata 2008, Pruyt and Kwakkel 2012). This computational approach, which we call the Adaptive Robust Design (ARD) approach, is proposed and illustrated below.

3.2.2. The Adaptive Robust Design approach

EMA is a methodology that uses computational experiments to combine plausible models and other uncertainties in order to generate a large variety of scenarios that are in turn used to analyze complex uncertain systems, support the development of long-term strategic policies under deep uncertainty, and test policy robustness over. EMA could also be used to develop adaptive policies under deep uncertainty since it allows for generating and exploring a multiplicity of plausible scenarios by sweeping multi-dimensional uncertainty space. EMA could then be used to identify vulnerabilities and opportunities present in this ensemble of scenarios, paving the way for designing targeted actions that address vulnerabilities or seize opportunities. The efficacy of the resulting policies could then be tested over the entire ensemble of scenarios. Moreover, EMA could be used to identify conditions under which changes in a policy are required. That is, it could help in developing a monitoring system and its associated actions. It thus appears that EMA could be of use in all adaptive policymaking steps.

Hence, our Adaptive Robust Design (ARD) approach starts along the lines of the EMA methodology with: (1) the conceptualization of the problem, (2) the identification of uncertainties (and certainties), and (3) the development of an ensemble of models that allows generating many plausible scenarios. It then proceeds with (4) the generation of a large ensemble of cases, where each case represents a realization of one specific future. Subsequently, (5) using scenario discovery (Bryant and Lempert 2010), this ensemble of cases is analyzed in order to identify troublesome and/or promising regions across the outcomes of interest, as well as the combination of uncertainties that cause these troublesome and promising regions. The next steps are: (6) the design –informed by the analysis in Step 5– of policies for turning troublesome regions into unproblematic regions, (7) the implementation of the candidate policies in the models, (8) the generation of all plausible scenarios subject to the candidate policies, (9) the exploration and analysis of the ensemble of scenarios obtained in Step 8 in order to identify troublesome and/or promising regions across the outcomes of interest, as well as the main causes of densely concentrated troublesome and/or promising regions, etc. Steps 5-8 should be iterated until (an adaptive) policy emerges with robust outcomes (see Figure 9).

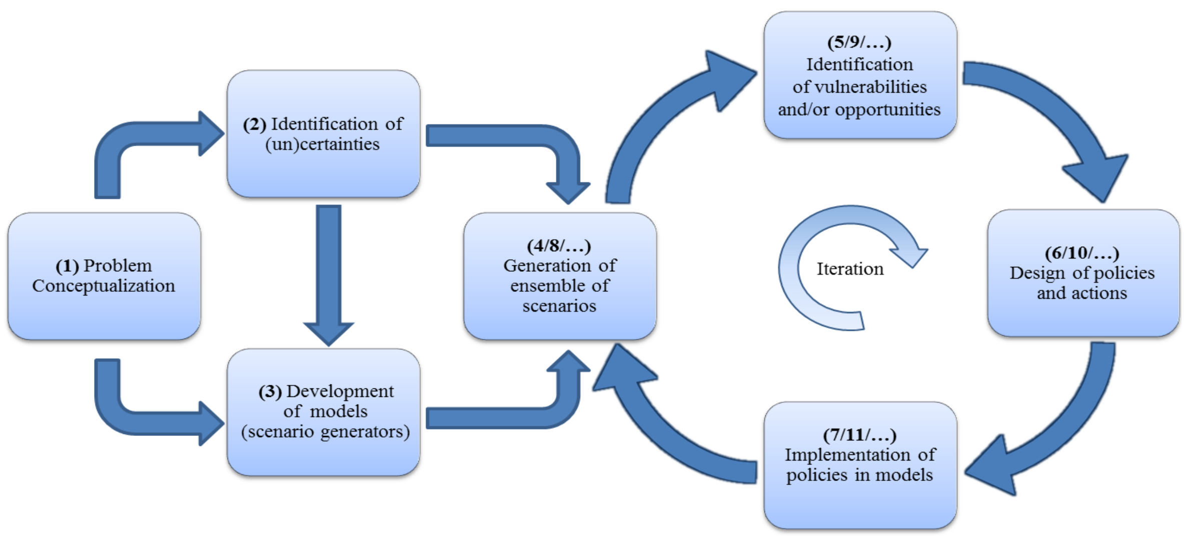

Figure 9: The Iterative Adaptive Robust Design process

The identification of troublesome and/or promising regions is crucial for this approach to be efficacious. These sub-regions of the uncertainty space represent combinations of uncertainties that either have highly negative or highly positive effects. The troublesome regions and the promising regions correspond respectively to vulnerabilities and opportunities in the adaptive policymaking framework. If uncertainties have a positive or negative effect across all the regions, then they are typically best addressed in the basic policy or through actions aimed at enhancing the robustness of the basic policy, while uncertainties of relevance only in particular regions are typically better handled through monitoring and associated corrective, defensive, or capitalizing actions.

In order to identify the troublesome and promising regions, we use an adapted version of the Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999, Lempert, Groves et al. 2006, Groves and Lempert 2007, Kwakkel, Auping et al. under review) –one that can deal with categorical and continuous uncertainties– which allows distilling uncertainty sub-spaces with high positive match ratios for a pre-specified binary classification function and with high relative masses (above a pre-specified threshold relative to the total scenario space). PRIM is particularly valuable as a scenario discovery algorithm for identifying troublesome subspaces of the multi-dimensional uncertainty space, and hence, for developing specific adaptive actions for adaptive policies. CART has been illustrated as an alternative scenario discovery algorithm in the previous chapter. Both PRIM and CART can be used to find regions of interest in the uncertainty space for designing policies that target such regions. Although PRIM requires more interaction than CART, as the regions identified by PRIM are easier to interpret, we have chosen to use only PRIM in this chapter.

PRIM has been used in combination with EMA by other authors (Lempert, Groves et al. 2006, Groves and Lempert 2007, Kwakkel, Auping et al. 2013). Those applications, however, aimed at translating the troublesome regions back to qualitative scenarios that could then be presented to a decision maker. Here, the troublesome and promising regions identified with PRIM are used directly for designing adaptive policies and the corresponding monitoring structures.

The approach for developing adaptive policies as presented here shares characteristics with 'Robust Decision-making (RDM)' (Lempert, Popper et al. 2003, Lempert, Groves et al. 2006, Lempert and Collins 2007, Bryant and Lempert 2010). Like in RDM, we emphasize the iterative character of policy formation. However, by connecting this to a particular framework for the design of adaptive policies, our approach is more specific on the various ways in which uncertainties can be handled through policies. Related to this, the approach focuses not solely on the negative side of the uncertainties, but also explicitly considers the opportunities that uncertainties can present. Another difference is that RDM relies on the notion of regret and uses a modified version of the expected utility framework (Lempert and Collins 2007), our approach does not entail such a stance. We use a robustness metric similar to signal-to-noise ratio, where mean is divided by standard deviation. Finally, in the exemplary paper on RDM (Lempert, Groves et al. 2006), there is a need for significant computational power due to sampling techniques used, whereas through the utilization of computationally more efficient methods such as PRIM, more efficient sampling techniques can be employed.

3.3. Case: The ARD Process Elucidated

3.3.1. Introduction to the Energy Transitions case

In order to illustrate how the ARD approach helps in designing adaptive policies, we present an illustrative case study about developing an adaptive policy for stimulating the transition of the electric power generation sector toward a more sustainable one. Transitions are large systematic societal transformations that, in general, are characterized by long periods over which they play out. Energy transitions are characterized by many deep uncertainties related to transition mechanisms, to the various competing technologies, and to human and organizational decision-making (Störmer, Truffer et al. 2009). Here we focus on the competition between technologies.

In order to achieve a sustainable future, there is a strong need for a transition in many domains, including transportation, housing, water and energy (Martens and Rotmans 2005). Energy is a crucial domain in which a fundamental transition toward clean generation technologies is desirable (Loorbach, Frantzeskaki et al. 2010) for environmental and security reasons. The current energy system is mainly dominated by fossil energy generation technologies, which are being challenged by rapidly evolving emerging technologies. Although new sustainable energy technologies are entering the market, their contribution to the total amount of energy generation is still relatively small. Transition of the energy system toward sustainability depends on the developments related to new technologies.

Such developments are typically characterized by nonlinearity and uncertainty regarding technological characteristics and market adoption (Abernathy and Clark 1985, Rip 1995). For example, precise lifetimes of technologies are not known and expected values are used in planning decisions. In addition, since the installation of new capacity mostly happens in large chunks, planning is complex and happens under uncertainty, and construction times are open to surprises affecting the actual completion time. Other important uncertainties are related to learning effects on costs and technological performance. Costs and technological performance, and expectations related to them, in turn influence the adoption and survival of technologies during the transition. These uncertainties play a crucial role and need to be taken into account when analyzing the dynamics of energy transitions and when trying to influence them by means of adaptive policies.

In order to explore the problem and the uncertainties of energy transitions, a System Dynamics (Forrester 1961, Sterman 2000) model developed for exploring the dynamics of energy systems transitions (Pruyt, Kwakkel et al. 2011) is used in this study which is the same SD model used in Chapter 2. The SD model incorporates, at a high level of aggregation, the main structures driving the competition among four energy technologies. Technology 1 represents old dominant non-renewable technologies. The other three technologies are at the start of the simulation relatively new, more sustainable, and more expensive. Since fast and relatively simple models are needed for EMA, the more sustainable technologies (2, 3 and 4) are considered generic for the sake of simplicity. The four technologies compete with each other in order to increase their share of energy generation, driven by mechanisms such as total energy demand, investment costs and the effect of learning curves on costs. A more detailed explanation of the model can be found in (Pruyt, Kwakkel et al. 2011). Moreover, the uncertainties taken into consideration and their corresponding ranges are displayed in Table 12.

.

Table 12: Overview of the uncertainties

Uncertainties	Description	Type	Range or Categories
Initial capacities	Starting value of the installed capacity of a technology	Parametric	Varying between 1 and 16000 MW for different technologies
Lifetimes	Expected lifetime of a technology	Parametric	Varying between 15 and 50 years for different technologies
Delay orders of lifetimes	Orders of the decommissioning delays	Categorical	1^{st}, 3^{rd}, 10^{th}, 1000^{th}
Initial decommissioned capacities	Initial values of the total decommissioned capacities of the technologies	Parametric	Varying between 10 and 10,000,0000 MW for different technologies
Planning and construction periods	Average period for planning and constructing new capacity for a technology	Parametric	Varying between 1 and 5 years for different technologies
Progress ratios	Ratio for determining cost reduction due to learning curve	Parametric	Varying between 70% and 95% for four different technologies
Initial costs	Initial investment cost of new capacity of a particular technology	Parametric	Varying between €500000 and €10 million per MW
Economic growth	Economic growth rate	Parametric	Randomly fluctuating between -0.01 and 0.035 (smoothed concatenation of 10-year random growth values)
Investment preference structures	Preferences criteria and weights for investing in new capacity of each of the technologies	Parametric weights & categorical switches	Preference for (more) familiar technologies [called here the Preference 'Against unknown']; Preference for (higher) expected progress; Preference for (higher) 'CO_2 avoidance'; Preference for (lower) 'Cost per MWe'

3.3.2. Results without policy

In order to explore the behavior of the simulation model over a wide variety of conditions, we utilize a workbench that is written in Python (Van Rossum 1995) which controls Vensim through its Dynamic Link Library (Ventana Systems Inc. 2010, Ventana Systems Inc. 2011). Using Latin Hypercube Sampling (LHS) (McKay, Beckman et al. 1979), a 'no policy' ensemble of 10,000 simulations[7] was generated. In the model used, at least one preference criterion must be activated (switch value equal to 1) for each run, else the run needs to be excluded: out of 10,000 simulations, 651 cases were excluded for that reason. Figure 10 shows the results of 1,000 randomly selected cases out of the remaining 9349 runs in the post-processed 'no policy' ensemble. The figure shows the behavior over time for the outcome indicator 'fraction of new technologies of total energy generation' as well as the Gaussian Kernel Density Estimates (KDEs) (Eric Jones, Travis Oliphant et al. 2001) of the end states.

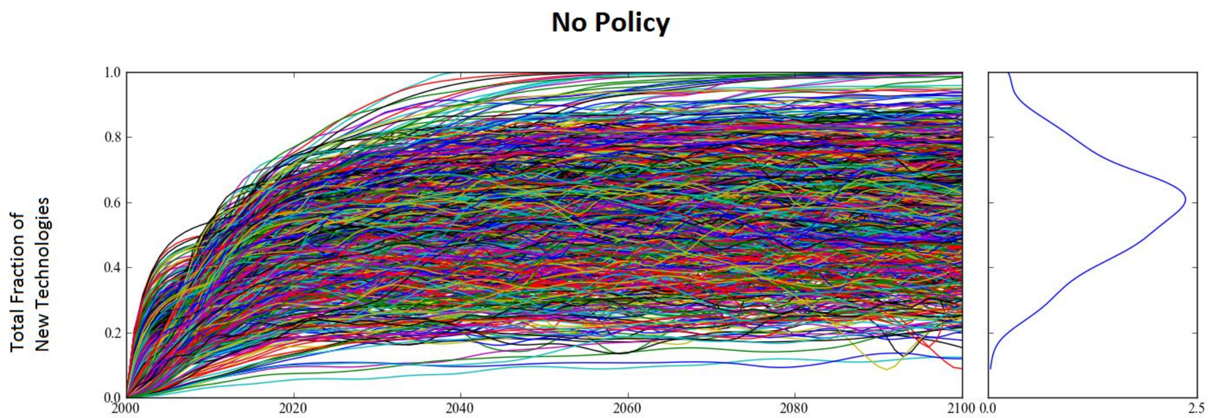

Figure 10: Total fraction of new technologies for the 'no policy' ensemble

These results show that the fraction of new technologies seems to be concentrated around 60% of total generation capacity by the simulated year 2100, which means that over the 100-year simulation time, the fraction of new technologies remains below 60% for about half of the runs. If the goal is an energy transition toward sustainability, then this ensemble as a whole is unlikely to be acceptable and requires policy intervention. Hence, we use PRIM to identify relatively large regions in the uncertainty space that generate relatively high concentrations of undesirable results, and the combinations of uncertainties and their values that lead to these regions. To this end, the end states for the total fraction of new technologies are classified as 1 if the fraction is below 0.60 and 0 otherwise Using PRIM; three troublesome uncertainty sub-spaces that contain at least 70% of the cases of class 1 are identified. These regions are characterized by specific combinations of uncertainties: Table 13 shows the full range of the uncertainties (first row), and the uncertainty ranges for each of these troublesome regions (other rows). Since PRIM seeks for regions in the uncertainty space with specific characteristics, not all of the uncertainties but only the uncertainties that determine the sub-spaces are shown. The lower range of the 'lifetime of Technology 1' is relevant for all three sub-spaces, i.e. the adoption of new sustainable technologies is hampered –in combination with the other uncertainties of the sub-spaces– by longer lifetimes of the dominant technology. Although a low performance of Technology 2 on the 'CO_2 avoidance' criterion, a high performance of Technology 1 on the 'expected cost per MWe' criterion, a short lifetime for

[7] Although we used the same SD model as in the previous chapter, we ran a bigger set of experiments as we had more computational power and improved computational scripts used for analysis.

Technology 3, and a short planning and construction time for Technology 1 also hinder the transition toward sustainability, none of these uncertainties and their ranges are as unambiguous as the lifetime of Technology 1 (for all regions, not the lower ranges). Shortening the lifetime of Technology 1 therefore seems to be promising, i.e. a policy design that is implemented in this analysis into the basis policy design.

Table 13: PRIM results for the no policy ensemble

	Preference against unknown		Average planning & const. period Tech. 1		Lifetime of Tech. 1		Lifetime of Tech. 3		CO_2 avoidance performance of Tech. 2		Expected cost per MWe performance of Tech. 1	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Original	2	5	1	5	30	50	15	40	1	5	1	2
Region1	2	5	1	5	34.4	50	15	37.5	1	4.2	1.1	1.8
Region2	2	5	1	4.8	33.7	50	15	37.5	1	4.4	1.1	2
Region3	2.9	4.9	1	4.5	32.6	50	16.3	40	1	5	1.2	2

3.3.3. Basic adaptive policy

Shortening the lifetime of Technology 1 could be achieved by increasing its decommissioning, for as long as the fraction of new technologies remains below a particular target fraction, say 0.8, assuming that 80% is a reasonable target for the fraction of sustainable technologies. To assess the performance of this basic policy, the same 9,349 experiments used for exploring the no policy case are now executed with the basic policy. Figure 11 displays the envelopes spanning the upper and lower limits of the total fraction of new technologies for the no policy ensemble (in blue) and the basic policy ensemble (in green) as well as the KDEs of the end states of all runs in the respective ensembles.

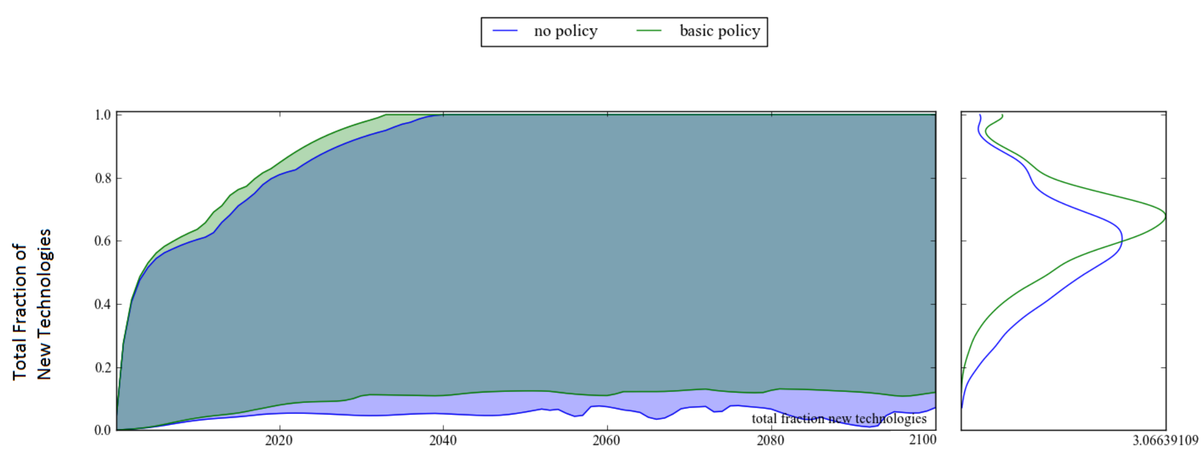

Figure 11: Comparison of no policy and basic policy for total fraction of new technologies

The upward shift of the sustainable fraction in Figure 11 means that the need for new capacity resulting from the additional decommissioning of Technology 1 is to a large extent filled by new technologies. Hence, the basic policy stimulates the transition from Technology 1 to new technologies, at least to some extent. Although there is an improvement in terms of the fraction of sustainable technologies, there is still room for further improvement. Many runs still end below the 60% new technologies threshold. For this reason, we applied PRIM once more with the same classification rule in order to identify troublesome regions for the basic policy.

The basic policy aimed at increasing the decommissioning of the dominant technology, since all PRIM boxes indicated decreasing the negative effect of the lifetime of Technology 1 would help to increase the fraction of new technologies. The second iteration PRIM results show there are three very different troublesome regions in the basic policy ensemble: The first region relates to the performance of the technologies on the CO_2 avoidance criterion, the second region relates to the underperformance of Technology 2, and the third region is determined by uncertainties related to economic growth and expected progress.

3.3.4. Robust policy

To redesign and improve the basic policy, it is necessary to analyze the characteristics of the PRIM regions to identify the vulnerabilities that generate the undesirable outcomes. The main drivers of the first region are the CO_2 avoidance performance values for Technology 1, 2, and 3. If the CO_2 avoidance performance of the dominant technology is high, while it is low for the new technologies, then transition toward new technologies is limited. Additionally, the region shows that higher performance for expected cost per MWe of the dominant technology also limits the transition. This outcome is not undesirable: it means that the old dominant technology outperforms the other technologies in terms of expected investments costs *and* CO_2 avoidance, which, in our case (not considering long-term security of supply), serves the same goal as the transition. Hence, it is not necessary to design a strategy for this region; this uncertainty sub-space consists of acceptable scenarios in terms of CO_2 avoidance even though the transition to new technologies is limited.

The second region is mainly driven by uncertainties related to Technology 2. A shorter lifetime, lower performance of CO_2 avoidance, and longer planning and construction period for Technology 2, lead to low fractions of sustainable technologies. The results indicate that Technology 1 becomes more preferable than Technology 2, which is initially the main alternative to Technology 1. In this situation, a reasonable defensive action would be to focus on the other sustainable technologies, in order to promote the transition toward these technologies instead. To address this vulnerability, a signpost tracking the progress of Technologies 2, 3 and 4 could be used. The point where the performance of Technology 3 or 4 equals the performance of Technology 2 could be the trigger for this signpost. Using this trigger, the corrective action would be to stop investing in Technology 2 and to shift investments to Technologies 3 and 4 instead. Therefore, we modified our basic policy by adding the monitoring and corrective actions and reran the experiments. Although the end state of the total fraction of new technologies does not improve much, the installed capacities of

Technologies 3 and 4 increase. This means that the defensive action developed for the second region served its purpose by steering the commissioning toward Technologies 3 and 4.

The third region shows that certain combinations of economic growth factors and preference for the expected progress criterion may also hinder the energy transition. Each of the economic growth parameters indicated in the third region corresponds to the value of economic development for ten years and together they constitute the overall behavior of economic development over 100 years. Although it is difficult to interpret the combination of these economic growth parameters, one could conclude that certain combinations of these parameters hinder the breakthrough of new technologies. Since the way in which economic development is represented in this model creates cyclic behavior, a possible corrective action could be to partly decouple the adoption of new technologies from the economic cycle with the help of subsidies and additional commissioning of new technologies. For this purpose, we use the investment cost of new technologies as a signpost. A possible defensive action would be to subsidize one or more sustainable technologies for some time to make them competitive. Hence, the costs of Technology 2, 3 and 4 are monitored over time and when their costs are close enough to the cost of the dominant technology, a 20% cost reduction of the new technologies is triggered over a period of 10 years. To further address this vulnerability, we also add a hedging action to the basic policy in the form of additional commissioning of Technologies 3 and 4 in their early years. These actions together aim at making the sustainable technologies more cost efficient once their costs are reasonably affordable levels, and to promote the transition toward new technologies in their early years. The economic action is successful in promoting sustainable technologies and increasing the total fraction after the first 10 years (around 2020). The adoption of the new technologies in later years is also higher than under the basic policy, suggesting that these cost reductions are effective.

To improve the performance of the adaptive policy even further, the triggers used for adaptivity were optimized using robust optimization (Ben-Tal and Nemirovski 1998, Ben-Tal and Nemirovski 2000, Bertsimas and Sim 2004). Using the trigger values optimized over the entire ensemble for the actions previously discussed significantly improves the adaptive policy. Figure 12 shows a comparison in terms of the *total fraction of new technologies* of the 'no policy' ensemble, the 'basic policy' ensemble, and this 'adaptive policy' ensemble over the same uncertainty space, i.e. using the same experimental design.

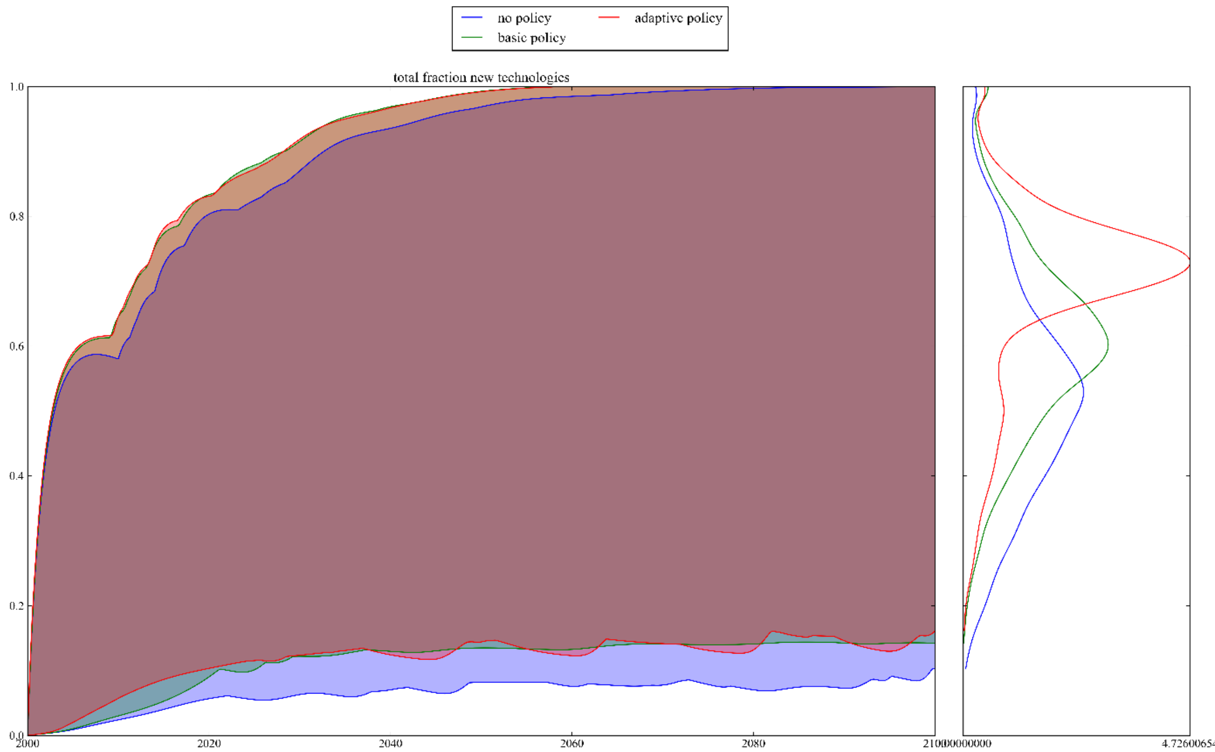

Figure 12: Comparison of no policy, basic policy and adaptive policy for total fraction of new technologies

It shows that the 'adaptive policy' ensemble, although hardly improving the extremes, outperforms the 'basic policy' and 'no policy' ensembles on this key performance indicator. The adaptive policy is a better guarantee for a successful transition towards new technologies under deep uncertainty. The distribution of the end values for adaptive policy (in red) shows that there are more runs that have higher fractions of new technologies.

3.4. Conclusions

In this chapter, we proposed an iterative computational approach for designing adaptive policies that are robust under deep uncertainty. The proposed approach has been illustrated on an energy transition case. Several of our findings warrant further discussion.

An important issue relates to the hedging action of Tech 3 and 4, and the monitoring of the costs. Figure 12 shows that these actions are effective in the early years, but lose their effect after 2020 due to the time-restricted nature of the hedging action. However, it is not possible to conclude that this reduction in effectiveness is caused only by the nature of the hedging action. The figure allows only seeing the bandwidth of the outcome but not revealing the dynamics over time. To reveal the underlying mechanism leading to a decline after 2020, it is necessary to identify those runs that improve around 2020 and then collapse. A modified classification in combination with PRIM could be utilized for such an analysis.

This study also has implications for Future-Oriented Technology Analysis (FTA). Transitions represent large structural and systematic transformations and the transition toward a more sustainable energy generation system is a grand societal challenge. This study shows how EMA and the proposed iterative Adaptive Robust Design approach can be employed for shaping and steering transitions toward more sustainable energy systems. Thus, this study is in line with the purpose of FTA projects that aim at developing long-term, adaptive, and robust policies for socio-economic and technological changes (i.e. energy transitions). This study illustrated the potential of EMA for FTA as suggested by Porter et al. (2004).

Uncertainties and surprises are inevitable and intrinsic to FTA projects. The adequate handling of uncertainty is thus of prime importance. Using FTA for planning for action is one area where the handling of uncertainty is crucial. Here, the goal should be to aim for plans that are adequate across the multiplicity of plausible future worlds. This chapter shows a way in which EMA can be utilized to support the iterative development and refinement of adaptive policies in light of a clear exploration of the multiplicity of plausible futures. That is, the chapter offers a new technique for FTA practitioners in their work of supporting long-term planning.

Another important challenge in many FTA projects is supporting a multi-actor process. Different perspectives, different worldviews or different mental models of various stakeholders are usually the norm in FTA projects and may result in situations where the results of FTA projects are contested by one or more of the actors involved in the process if the diversity of views and/or actors is not properly cared for. Here, EMA can be of use, since EMA allows incorporating a multiplicity of perspectives, worldviews, mental models or quantitative models. That is, EMA could be used to support an inclusive modeling process from the start, where different beliefs about how a system functions, or which aspects of a problem are important, are explicitly taken into account and assessed for their consequences.

We have proposed an iterative model-based approach for developing adaptive policies under uncertainty. The proposed approach, which we call Adaptive Robust Design, has been illustrated through a case about the structural and systemic transformation of energy generation systems toward a more sustainable future. Our analysis shows that ARD can be used to develop long-term, adaptive and robust policies for grand societal transformations. Furthermore, this study has shown that Exploratory Modeling and Analysis can be utilized successfully in the context of adaptive policymaking. The iterative approach for designing robust adaptive policies helps to identify and address both vulnerabilities and opportunities, resulting in a dynamic adaptive policy that improves the extent to which the energy system transits to a more sustainable functioning.

There is a growing awareness about the need for handling uncertainty explicitly in decision-making. The recent financial and economic woes have rekindled a wider interest in approaches for handling uncertainty. However, there is also a certain degree of skepticism about the extent to which models can be used for decision-making under uncertainty. In addition, all the extant forecasting methods contain fundamental weaknesses and struggle deeply in grappling with the long-term's multiplicity of plausible futures. The presented case illustrates how models can be used to support decision-making, despite the presence of a wide variety of quite distinct uncertainties and a multiplicity of plausible futures. A central idea in this approach is to use the available models differently, instead of using them in a predictive manner and ignoring many uncertainties. The models were used here to explicitly explore a plethora of uncertainties in order to assess the implications of these uncertainties for decision-making.

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In the previous chapter, we have introduced the Adaptive Robust Design (ARD) approach, robust optimization and how it can be used together with ARD approach. Robust optimization has helped design robust policies that can deal with deep uncertainty in the policymaking. It is also crucial to deal with the multiplicity of possibly conflicting objectives in the policy design.

Now, we will introduce how to use multi-objective optimization and illustrate how useful it can be for policy design. Together with robust optimization, next chapter demonstrates how multi-objective robust optimization approach helps alleviate the problem of multiple objectives with diverging preferences.

Chapter 4 - ARD & Multi-Objective Robust Optimization[8]

4.1. Introduction

Policymaking for complex adaptive systems requires dealing with dynamic complexity and deep uncertainty. Complex adaptive systems are composed of interacting heterogeneous agents that act independently, interact with each other, and adapt their behavior over time (Miller and Page 2009, Desouza and Lin 2011). Out of these interactions, emerge global regularities that show dynamic behavior over time due to the intrinsic adaptations taking place by the individual heterogeneous agents. The result of this is that when making policy for complex adaptive systems, one is confronted by intrinsic unpredictability (Desouza and Lin 2011). Various traditional approaches have been proposed to improve policymaking. There are two main analytical reasons why traditional approaches for policymaking mostly do not perform satisfactory when applied to complex adaptive systems. First, traditional planning approaches start from predicting the future and preparing a plan for meeting this future (Quay 2010). Second, the typical plan is static and not designed to be changed over time (Walker, Rahman et al. 2001, Albrechts 2004, Wilby and Dessai 2010, de Neufville and Scholtes 2011). Due to their nature, static policies based on predictions of the future are ineffective and inappropriate for dealing with complexity under uncertainty. Hence, there is a need for innovative approaches for dealing with complexity and uncertainty, especially deep uncertainty.

Deep uncertainty is encountered when the different parties to a decision do not know or cannot agree on the system model that relates consequences to actions and uncertain model inputs (Lempert, Popper et al. 2003), or when decisions are modified over time (Hallegatte, Shah et al. 2012). In these cases, it is possible to enumerate the possibilities (e.g. sets of model inputs, alternative relationships inside a model, etc.), without ranking these possibilities in terms of perceived likelihood or assigning probabilities to the different possibilities (Kwakkel, Walker et al. 2010).

Policies that can be adapted over time in response to how the uncertainties resolve have been suggested as a way of improving the performance of policies in the presence of deep uncertainty (Walker, Marchau et al. 2010). The idea of adaptivity dates back almost a century ago. Dewey (Dewey 1927) suggested that policies could be used as experiments that can stimulate learning and adaptation, allowing the policy to evolve based on experience (Busenberg 2001). Early applications of adaptive policies can be found in the field of environmental management (Holling 1978, McLain and Lee 1996). Policies are designed from the outset to test well-formulated hypotheses about how the behavior of an ecosystem will react to human actions (Lee 1993). A similar attitude is also

[8] This chapter is largely based on the publication *Hamarat, C., J. H. Kwakkel, E. Pruyt and E. T. Loonen (2014). "An exploratory approach for adaptive policymaking by using multi-objective robust optimization."* Simulation Modelling Practice and Theory 46 (2014): 25-39.

advocated by Collingridge (Collingridge 1980) with respect to the development of new technologies. Given ignorance about the possible side effects of technologies under development, he argues that one should strive for correctability of decisions, extensive monitoring of effects, and flexibility.

Over the last few years, substantial work has been done on the design of adaptive policies in a variety of policy domains. In transport policy, (Walker, Rahman et al. 2001, de Neufville and Odoni 2003, Kwakkel, Walker et al. 2010) all put forward adaptive planning approaches for airports, (Marchau and Walker 2003, van der Pas, Marchau et al. 2010, van der Pas, Kwakkel et al. 2012) put forward adaptive policies for the implementation of intelligent speed adaptation measures, and more broadly (Marchau, Walker et al. 2009) outlines the benefits of adaptive policies for transport policy in general. In water resources management, examples of adaptive policymaking include (Dessai and Hulme 2007, Matrosov, Padula et al. 2013, Matrosov, Woords et al. 2013). In climate adaptation, (Dessai, Hulme et al. 2009, Hallegatte 2009, Lempert and Groves 2010, Haasnoot, Middelkoop et al. 2012, Hall, Brown et al. 2012, Haasnoot, Kwakkel et al. 2013, Weaver, Lempert et al. 2013) all argue for adaptive policies. A common theme running through this work in different policy domains is that one should take only those actions that are non-regret and time-urgent and postpone other actions to a later stage (Walker, Haasnoot et al. 2013). However, in none of this work so far, a method has been put forward for identifying when to adapt the policy (IISD 2006, Walker, Marchau et al. 2010, Hamarat, Kwakkel et al. 2013).

It has been argued that computational modeling approaches are promising for designing adaptive policies (Bankes 2002, Dessai, Hulme et al. 2009, Desouza and Lin 2011). Various model-based decision support techniques have been put forward that can be used to support the design of adaptive policies. These include Robust Decision-making (RDM) (Lempert 2002, Lempert, Popper et al. 2003, Lempert and Groves 2010), Info-gap decision theory (Ben Haim 2006), Real options (de Neufville and Scholtes 2011) and Adaptive Robust Design (Hamarat, Kwakkel et al. 2013). There is an emerging literature comparing and contrasting these different approaches (Hall, Lempert et al. 2012, Matrosov, Padula et al. 2013, Matrosov, Woords et al. 2013, Walker, Haasnoot et al. 2013).

Here, we focus on Adaptive Robust Design, which in essence combines RDM with an explicit framework for adaptive policies (Hamarat, Kwakkel et al. 2013, Walker, Haasnoot et al. 2013). Of central importance to adaptive policymaking is the idea that future actions are activated only if and when necessary. That is, the design of a monitoring system with associated trigger values for activating pre-specified actions is at the heart of adaptive policymaking. The outlined approach can be used to identify the conditions under which changes in the policy are required. However, this leaves unresolved the question at which trigger values actions should best be activated. The challenge here is finding an appropriate balance between activating actions too early and too late. Specifying appropriate trigger values is further complicated by the presence of different stakeholders with different preferences. A good trigger value for one actor might be far from ideal for another. This chapter specifically addresses the problem of specifying good trigger values in the presence of multiple stakeholders with different preferences.

When a simulation model is used to find the optimum input parameters of a given system to determine expected performance, this is called simulation optimization (Pierreval and Paris 2003, Andradóttir 2007). The literature on model-based decision support for adaptive policymaking has ignored the use of simulation optimization until very recently. It has been argued that optimization is impossible because of uncertainty and the presence of multiple stakeholders with diverging preferences (Lempert, Groves et al. 2006). Kasprzyk et al. (Kasprzyk, Nataraj et al. 2013) used a simulation optimization approach to identify feasible designs, the robustness of which was subsequently tested using RDM; and Matrosov et al. (Matrosov, Padula et al. 2013) compared economic optimization with RDM and argued that these approaches should somehow be combined. In this chapter, we build on this work. We argue that the problem caused by uncertainty can be addressed using robust optimization and adopting a multi-objective optimization approach can alleviate the problem caused by the presence of multiple stakeholders with diverging preferences. More specifically, we argue that the problem of identifying when to adapt a policy can be addressed through multi-objective robust optimization. We demonstrate this multi-objective robust optimization approach with a case study of the design of an adaptive policy for steering the transition of the EU energy system towards a more sustainable functioning. Our work thus differs from (Kasprzyk, Nataraj et al. 2013) in that we include the robustness analysis inside the simulation optimization approach, and as such we follow the suggestion of (Matrosov, Padula et al. 2013) on combining simulation optimization and RDM.

The rest of this chapter is structured accordingly. Section 4.2 presents more details on the methodology. Section 4.3 introduces details on the case and simulation model used. Section 4.4 presents the results. Section 4.5 contains our concluding remarks.

4.2. Methodology: Multi-Objective Robust Optimization

Vulnerabilities and opportunities are central concepts in adaptive policymaking. In order to design robust policies, it is crucial to identify combinations of uncertainties that have a substantial positive (opportunity) or negative (vulnerability) influence on the degree of goal achievement. Targeted actions can then be designed to either take advantage of the opportunity, or reduce the effect of the vulnerability. Such actions can be taken immediately, or at some future point in time when the conditions warrant it. The Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999, Groves and Lempert 2007, Kwakkel, Auping et al. 2013) can be used for discovering vulnerabilities and opportunities. PRIM can be used for data analytic questions, where the analyst tries to find combinations of values for input variables that result in similar characteristic values for the outcome variables. Specifically, one seeks one or more subspaces of the model input space within which the value of an outcome of interest is considerably different from its average value over the entire model input space. PRIM describes these subspaces in the form of hyper-rectangular boxes of the model input space. It has been shown that the results of PRIM could be enhanced significantly by preprocessing the data with Principal Component Analysis (PCA) (Dalal, Han et al. 2013). In this chapter, we use PCA PRIM for identifying vulnerabilities and opportunities.

The adaptive part of an adaptive policy or plan takes the form of a monitoring system that specifies what information should be tracked, and under which pre-specified conditions pre-specified actions will be taken (Walker, Rahman et al. 2001, Kwakkel, Walker et al. 2010). A signpost is the information, which is tracked to decide whether it is necessary to take actions and a trigger is the critical value of a signpost that triggers to take actions. These signposts and triggers are defined during the contingency planning phase in adaptive policymaking. The efficacy of an adaptive plan hinges on the care with which the contingency planning is carried out. In the current adaptive policymaking literature, the values used for triggers are mostly based on logical guesses, expert opinions, or historical data (McDaniels, Mills et al. 2012). Given the importance of the monitoring system for the overall efficacy of an adaptive policy, there is a need for a more substantial way of determining appropriate trigger values. The use of optimization can be a possible solution for this problem.

Optimization is widely used in various aspects of policymaking and in fields ranging from engineering to science, and from business to daily life. Optimization mostly refers to finding the optimum solution among a set of plausible alternatives under given constraints. However, this approach might be misleading for policymaking under deep uncertainty where optimizing a single goal is not the main aim (Bankes 2011). Under deep uncertainty, one best solution among a set of possible alternatives without violating the given constraints, i.e. an optimal solution, usually does not exist (Rosenhead, Elton et al. 1973, Bankes 2011). A field within optimization that allows to overcome the difficulties posed by uncertainty is robust optimization (Bertsimas, Brown et al. 2011). Robust optimization methods aim at finding optimal outcomes in the presence of uncertainty (Ben-Tal and Nemirovski 2000, Bertsimas and Sim 2004, Dellino, Kleijnen et al. 2010). Adaptive policymaking requires proper handling of both parametric and structural uncertainties in order to develop robust policies. Therefore, robust optimization methods can be of great use for adaptive policymaking (Gabrel, Murat et al. 2013).

The use of computational simulations for analyzing dynamic systems helps gather significant information about the system of interest (Pierreval 1992). More specifically, simulation is used for evaluating the performance of complex systems (Andradóttir 1998). In the simulation optimization field, several approaches have been proposed (Azadivar 1999, Fu 2002, Fu, Chen et al. 2008), although many of them assume a certain or fixed environment (Dellino, Kleijnen et al. 2010). However, improper handling of uncertainty may result in undesirable solutions. Given an uncontested objective function, uncertainty can affect either or both the constraints and the score on the objective function (Beyer and Sendhoff 2007, Gabrel, Murat et al. 2013). Several approaches have been proposed to handle uncertainty in simulation optimization (Schuëller and Jensen 2008, Dellino, Kleijnen et al. 2010, Dellino, Kleijnen et al. 2010, Kleijnen, Pierreval et al. 2011). The basic idea shared by these approaches is that the uncertainties are somehow directly incorporated in the optimization problem. There are at least three distinct ways in which this can be done (Schuëller and Jensen 2008), namely (i) the direct simulation approach where the robustness measures are calculated by repeatedly running the simulation model (e.g. (Nejlaoui, Houidi et al. 2013)); (ii) the metamodel approach where the results of a simulation model are approximated using a metamodel (e.g. (e.g. Dellino, Lino et al. 2009, Dellino, Kleijnen et al. 2010, Dellino, Kleijnen et al. 2010)); and (iii) the stochastic approximation approach where the values of the random functions are used directly in the optimization algorithm (Al-Aomar 2006). In this chapter, we adopt a direct simulation approach and are interested in the situation where the uncertainty affects the objective function.

In robust optimization, robustness can be operationalized in many different ways. Rosenhead et al. (1973) understand robustness as flexibility, that is, as leaving options open. Other ways of operationalizing robustness include Wald's minimax criterion, which chooses the decision alternative that minimizes the maximum risk (Wald 1945); Minimax regret (Savage 1951), which results in choosing the solution with the least maximum regret (Lempert, Popper et al. 2003); and various forms of satisficing (Simon 1955), such as risk discounting, and certainty equivalents (Rosenhead, Elton et al. 1973). With the direct uncertainty treatment, adaptive robust design resembles Monte-Carlo strategies where simulation techniques are used to obtain objective function values (Beyer and Sendhoff 2007).

Within the literature on computational support for designing adaptive policies, robustness has been defined in a number of ways such as the first order derivative of the objective function (McInerney, Lempert et al. 2012); as reasonable performance over a wide range of plausible futures (Lempert and Collins 2007, Hamarat, Kwakkel et al. 2013); as regret (Lempert, Popper et al. 2003, Kwakkel, Walker et al. 2012); and as sacrificing a small amount of optimal performance in order to be less sensitive to violated assumptions (Lempert and Collins 2007). This last definition bears a large similarity to the local robustness model employed in info-gap decision theory (Ben Haim 2006). Another approach, used for robust parameter design, is the signal-to-noise ratio, which can be simplified as mean divided by standard deviation (Madu and Madu 1999, Bérubé and Wu 2000). In this chapter, we will use an approach that is very similar to signal-to-noise ratio for our robustness scores.

For complex and uncertain systems where decision-making involves multiple stakeholders, it may be treacherous to design plans that are based on a single objective or objectives that are imprecisely merged into a single objective. Multi-objective optimization helps to grasp the multiplicity of different and possibly conflicting objectives. For mostly, there is no single solution for a multi-objective optimization problem because of trade-offs between the different objectives. If it is possible to assign precise and uncontested weights to the different objectives, then it might be possible to merge multiple objectives into a single overarching objective. However, it is often difficult to decide on the appropriate weights for different objectives in complex and uncertain systems, in particular when various stakeholders are involved. An alternative approach is to find a set of solutions that are not dominated. A given solution is non-dominated if there does not exist a solution that performs better on all criteria. These solutions are called Pareto optimal and the result of the optimization is not a single optimal solution but a set of solutions that, together, form the Pareto front. Multi-objective optimization has been used before for simulation optimization (Tekin and Sabuncuoglu 2004, Alrefaei and Diabat 2009, Dellino, Lino et al. 2009, Lin, Sir et al. 2013).

A general formulation of the multi-objective optimization problem is shown in Equation 1, where Ω is the total decision space, x the decision vector of decision variables in the decision space, F the multi-objective function, f_i the i^{th} objective function, c_i the i^{th} constraint function, $\mathcal{E}$ the set of equality constraints, and $\mathcal{X}$ the set of inequality constraints.

$$
\begin{array}{ll}
minimize_{x \in \Omega} & F(x) = [f_1(x), f_2(x), \ldots, f_m(x)] \\
 & \\
subject\ to & c_m(x) = 0, \forall m \in \mathcal{E} \\
 & c_n(x) \leq 0, \forall n \in \mathcal{X}
\end{array}
$$

Equation 1: The general multi-objective optimization problem. (Adapted from (Reed, Hadka et al. 2013)).

Several approaches have been developed to solve multi-objective optimization problems such as the weighted sum approach, the utility function method, the lexicographic method, goal programming, and Successive Pareto Optimization (Marler and Arora 2004, Mueller-Gritschneder, Graeb et al. 2009). Downsides of these approaches include the need for inter-criteria information, and the fact that they generate only a single solution at a time (Coello Coello 2006). Evolutionary algorithms that simultaneously generate populations of candidate solutions address both points. Such a population-based approach can be used for generating the solutions on the Pareto front in a single run of an evolutionary algorithm (Goldberg 1989). To this purpose, evolutionary algorithms can be beneficial for solving multi-objective optimization problems (Coello Coello 2006, Reed, Hadka et al. 2013). In this study, a well-established multi-objective evolutionary optimization technique, the Nondominated Sorting Genetic Algorithm-II (NSGA-II) (Deb, Pratap et al. 2002), is used.

In short, we are arguing that the problem of identifying appropriate conditions for adapting a policy can be resolved through multi-objective robust optimization. In this application, the decision space Ω is formed by the set of triggers, each of which can be subject to one or more constraints c_i. The multi-objective function F specifies the robustness for the different outcomes of interest. In this chapter, we use a signal-to-noise ratio as our robustness metric, but there is no principal reason that other metrics could not be used instead. This metric is computed over a specific number of scenarios. Similar approaches have been applied in other fields such as environmental systems and engineering design (Deb and Gupta 2006, Kasprzyk, Nataraj et al. 2013). The result of solving this optimization problem is an approximation of the Pareto front, containing a set of Pareto optimal, i.e. non-dominated, trigger values.

4.3. Case: An elaborated case on energy transitions

The European Union (EU) has targets for the reduction in carbon emissions and the share of renewable technologies in the total energy production by 2020 (European Commission 2010). The main aim is to reach 20% reduction in carbon emission levels compared to 2010 levels and to increase the share of renewables to at least 20% by 2020. However, the energy system includes various uncertainties related to technology lifetimes, economic growth, costs, learning curves, investment preferences and so on. For instance, precise lifetimes of technologies are not known and expected values are used in planning decisions. Furthermore, it is deeply uncertain how the economic conditions, which have a direct influence on the energy system, will evolve. Thus, it is of great importance to take these uncertainties into consideration when analyzing the energy system, and preparing policies for meeting the EU targets.

In order to meet the 2020 goals, the EU adopted the European Emissions Trading Scheme (ETS) for limiting the carbon emissions (European Commission 2010). ETS imposes a cap-and-trade principle that sets a cap on the allowed greenhouse gas emissions and an option to trade allowances for emissions. However, current emissions and shares of renewables show a fragile progress of reaching the 2020 targets. It is necessary to take additional actions for steering the transition toward cleaner energy production. This requires a better handling of the uncertainties in the energy system and more robust policies that can promote renewable technologies.

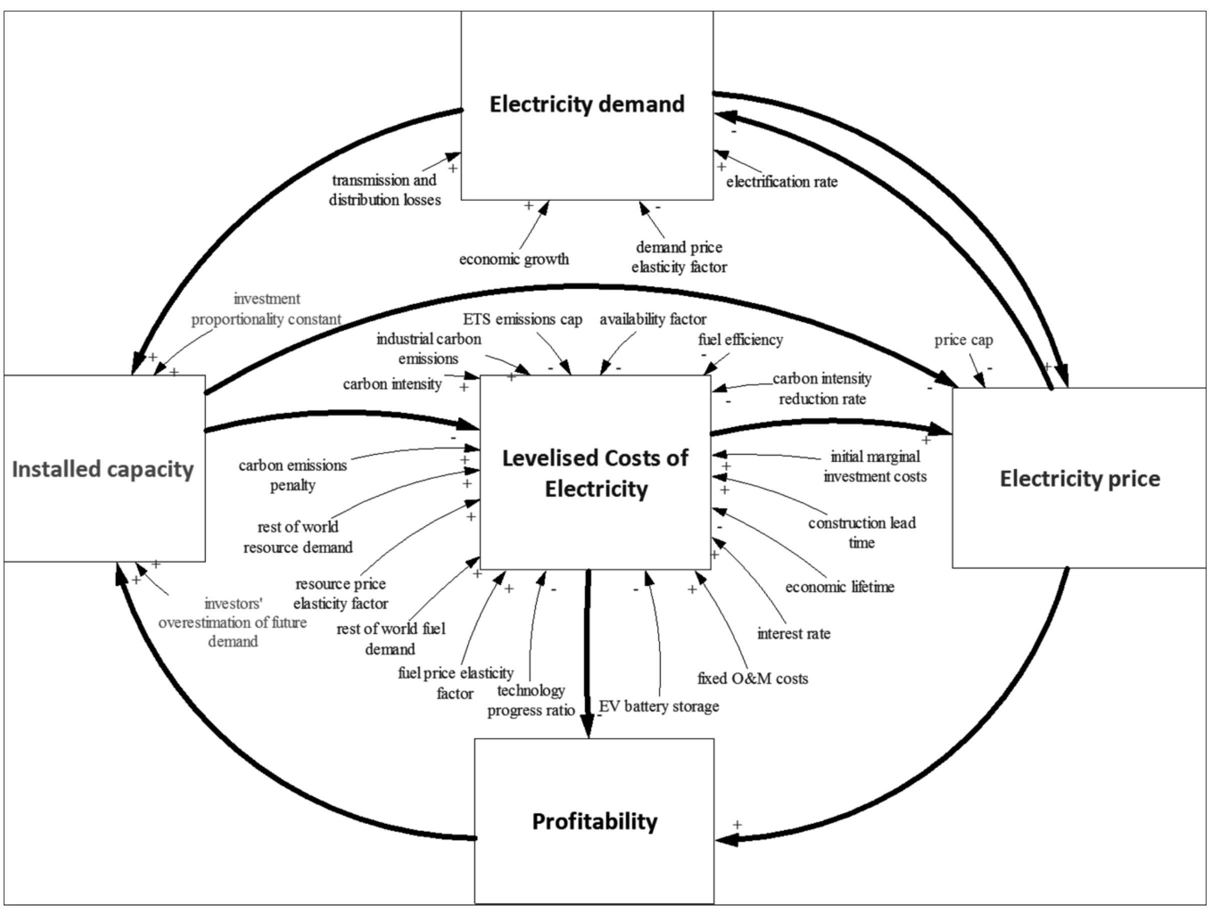

Figure 13: The main causal loop diagram of the EU energy model.

In this study, a System Dynamics (Forrester 1961, Sterman 2000, Pruyt 2013) model is used for simulating the plausible futures of the EU electricity system. The model represents the power sector in the EU and includes congestion on interconnection lines by distinguishing seven different regions in the EU. These are northwest (NW), northeast (NE), middle (M), southwest (SW), southeast (SE) of Europe, United Kingdom and Ireland (UKI) and Italy (I). Nine power generation technologies are included. These are wind, PV solar, solid biomass, coal, natural gas, nuclear energy, natural gas with Carbon Capture and Sequestration (CCS), coal gasification with CCS, and large-scale hydropower. The model endogenously includes mechanisms and processes related to the competition between technology investments, market supply-demand dynamics, cost mechanisms, and interconnection capacity dynamics. Not only endogenous mechanisms but also various exogenous variables are included. Figure 13 shows the main sub-models that constitute this model at an aggregate level. These are installed capacity, electricity demand, electricity price, profitability, and levelised costs of electricity. At an aggregated level, there are two main factors that drive new capacity investments: electricity demand and expected profitability. An increase of the electricity demand leads to an increase in the installed capacity, which will affect the electricity price. This will cause a rising demand, in turn resulting in more installed capacity. On the other hand, decreasing electricity prices will lead to lower profitability and less installed capacity, which will result in electricity price increases. Each sub-model has more detailed interactions within itself and with the other sub-models and exogenous variables and these causal relationships drive the main dynamics of the EU electricity system.

Figure 13 is a graphical representation of the causal relationships in the model. In order to run computational simulations, these relationships are translated into a system of differential equations, which are implemented in Vensim (Ventana Systems Inc. 2010). The model includes 33 ordinary differential equations, 499 auxiliary equations, and 632 variables. In this study, we are particularly interested in certain outputs and inputs. The output variables that we are interested in are the fraction of renewable technologies, the fraction of carbon emission reduction and the average total costs of electricity production. The differential equations for these outputs are given in Equation 2. It is beyond the scope of this chapter to include all the equations and variables separately. More detail on the model can be found in (Loonen 2012), including detailed descriptions of each equation and variable.

$$\text{Fraction of renewable technologies} = \frac{\sum_{i=1}^{7}\sum_{j_r=1}^{4}\left(\text{Power production}_{i,j}\right)}{\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Power production}_{i,j}\right)}$$

$$\text{Fraction of carbon emission reduction} = \frac{\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Carbon intensity}_{i,j} \times \text{Power production}_{i,j}\right)\text{ in 2010}}{\int_{2010}^{2050}\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Carbon intensity}_{i,j} \times \text{Power production}_{i,j}\right)dt}$$

$$\text{Average total costs of electricity production} = \frac{\int_{2010}^{2050}\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Producer costs}_{i,j}+\text{Policy costs}_{i,j}\right)dt}{\int_{2010}^{2050}\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Power production}_{i,j}\right)dt}$$

$$\forall i = 1,2,\dots,7\ (Regions\ in\ EU)$$
$$\forall j = 1,2,\dots,9\ (Technologies\ used)$$
$$\forall j_r = 1,2,3,4\ (Renewable\ technologies: Wind, PV, hydro, biomass)$$
$$t \in [2010,2050]$$

Equation 2: The equations for the output variable of interest

From a range of various deeply uncertain inputs, we are interested in exploring and analyzing their influence on the key output variables. In order to explore the uncertainty space, not only parametric but also structural uncertainties are included in the analysis. For exploring structural uncertainties, several alternative model formulations have been specified and a switch mechanism is used for switching between these alternative formulations. Parametric uncertainties are explored over pre-defined ranges. Table 14 provides an overview of the uncertainties, 46 in total, that are analyzed and their descriptions.

Table 14: Specification of the uncertainties to be explored

Name	Description
Economic lifetime	For each technology, the average lifetimes are not known precisely. Different ranges for the lifetimes are explored for each technology.
Learning curve	It is uncertain for different technologies how much costs will decrease with increasing experience. Different progress ratios are explored for each technology.
Economic growth	It is deeply uncertain how the economy will develop over time. Six possible developments of economic growth behaviors are considered.
Electrification rate	The rate of electrification of the economy is explored by means of six different electrification trends.
Physical limits	The effect of physical limits on the penetration rate of a technology is unknown. Two different behaviors are considered.
Preference weights	Investor perspectives on technology investments are treated as being deeply uncertain. Growth potential, technological familiarity, marginal investment costs and carbon abatement are possible decision criteria.
Battery storage	For wind and PV solar, the availability of (battery) storage is difficult to predict. A parametric range is explored for this uncertainty.
Time of nuclear ban	A forced ban for nuclear energy in many EU countries is expected. The time of the nuclear ban is varied between 2013 and 2050.
Price – demand elasticity	A parametric range is considered for price – demand elasticity factors.

4.3.1. Results: From ETS toward an adaptive policy

ETS is currently used in Europe to reduce carbon emissions. It introduces an annual cap on the maximum amount of emissions and the option for trading these carbon emission rights. The results of the ETS policy so far leave much to be desired. This creates the need to explore plausible futures under this policy and identify ways of complementing this policy in pursuit of the desired CO_2 reduction.

Using a workbench written in Python (Kwakkel and Pruyt 2013) which controls Vensim (Ventana Systems Inc. 2010), the model has been simulated 10,000 times to generate an ensemble of cases, generating time series between 2010 and 2050. Each case is a selection of 46 different uncertainties and certain assumptions about the future state of the system via Latin Hypercube Sampling (Pilger, Costa et al. 2005). The results of the ETS policy under uncertainty indicate that it is difficult to meet the 2020 targets through ETS only. For most futures, the fraction of renewables remains around 25% and the carbon emissions reduction fraction is around 10. It is obvious that there is a need for further actions in order to achieve a sustainable energy future.

Through scenario discovery using PCA PRIM, we identify the key vulnerabilities and opportunities of the ETS policy, in light of which the ETS policy can be redesigned. This analysis did not produce useful information with respect to vulnerabilities because there was no uncertainty combination identified by PCA PRIM that results in undesirable outcomes. However, there are useful findings related to opportunities that could be taken advantage of. PCA PRIM is used to identify the opportunities that can lead to futures where the fraction of renewables is higher than 40%. These opportunities are mainly related to technology lifetimes and the learning curves of the technologies. To be more precise, longer lifetimes of renewables, shorter lifetimes of non-renewables (especially coal and gas), and stronger learning effects for renewables are opportunities for achieving a more sustainable functioning. Hence, in order to improve the ETS system, three adaptive actions are added to the current ETS policy.

Action 1 aims at accelerating the phase out of the old non-renewable technologies. The gap between the desired and the current level of the renewable fraction is tracked. The desired level for 2050 is assumed to be 80%. This action introduces an additional decommissioning flow, factored by the gap, for non-renewable technologies.

Action 2 aims at making the renewable technologies more cost-attractive by introducing a subsidy fraction on the marginal investment costs of renewable technologies. The costs of the most expensive non-renewable technology and the renewable technologies are monitored. If the cost of a renewable is close to the most expensive non-renewable, here within 25% (proximity), then a subsidy of 25% is introduced for 10 years.

Action 3 aims at sustaining the targeted renewable fraction in the future. A forecast of the renewable fraction for 10 years ahead is made. A desired fraction is also assumed to be 80%. If the gap between the desired fraction and the forecast is bigger than the trigger level of 10%, non-renewable technologies are decommissioned with an additional percentage of 25%.

The resulting policy with these adaptive actions is called the adaptive policy. For testing the performance of the adaptive policy, it is again run for the same ensemble of 10,000 computational experiments. There is a remarkable improvement in policy performance. Figure 14 compares the ETS policy (in dark gray and dashed line) and the adaptive policy (in light gray and solid line) for three outcomes: the carbon emissions reduction fraction, average total costs, and the renewables fraction. The figure shows the envelopes of the outcomes (left) which span the upper and lower limits for 10,000 simulations over time and the Kernel Density Estimates (Eric Jones, Travis Oliphant et al. 2001) of the terminal values in 2050 (right) in the respective ensemble. The adaptive policy improves the fraction of renewables dramatically from 40% to 50% on average in 2020 and to 70% in 2050. Similarly, there are clear improvements in terms of the fraction of carbon emissions reduction and average total costs.

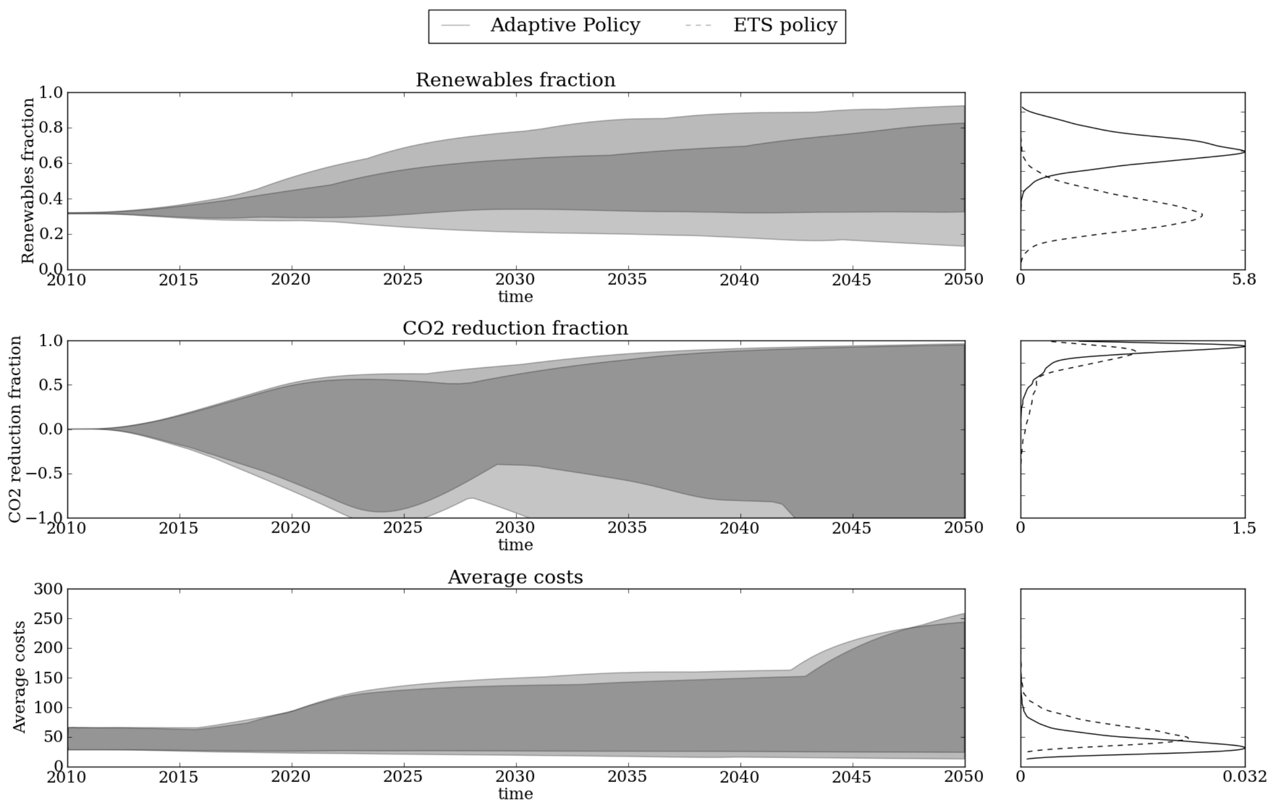

Figure 14: Comparison of ETS and Adaptive policies

4.3.2. Fine-tuning trigger values

For the multi-objective robust optimization, we use three objectives: (1) the fraction of renewable technologies, (2) the fraction of carbon emission reduction in 2050 compared to 2010, and (3) the average total costs of electricity production. The simulation model used in this study produces the values for these three objectives. The EU has specific targets for the share of renewable technologies and the reduction fraction of carbon emissions by 2020. Hence, these are the first two objectives. They are to some extent dependent and/or similar. However, the average total cost of electricity generation is dissimilar. While the first two objectives are to be maximized, the third objective is to be minimized.

In order to design an adaptive policy, signposts and triggers are used for ensuring the adaptivity and flexibility of the policy. The specification of the triggers is of a crucial importance for the performance of the adaptive policy. In the adaptive ETS policy, there are 8 components of 3 actions. In Table 15, these components, including the triggers, are given together with their brief descriptions and it also shows which trigger is part of which action.

Table 15: List of components and their descriptions

	Components	Brief Description
Action 1	Desired Fraction *(df)*	Trigger for the desired fraction of renewable technologies.
	Additional Decommissioning *(ad)*	Additional fraction of non-renewable technologies to be decommissioned.
Action 2	Subsidy Factor *(sf)*	Additional fraction of subsidy for renewables.
	Subsidy Duration *(sd)*	Duration for how long the subsidy for the renewables will be active.
	Proximity *(pr)*	Trigger for the proximity of cost to the cost of the most expensive non-renewable technology.
Action 3	Decommissioning Factor *(dcf)*	Fraction to be decommissioned for non-renewables when the gap between desired and forecasted fraction for renewables is above the Trigger.
	Forecast Time Horizon *(fth)*	Time horizon over which the forecast for the level of renewable fraction is done.
	Trigger *(tr)*	Trigger for the proximity of the forecasted renewable fraction to the desired fraction.

The robustness metric used here is based on the idea of increasing the expected outcomes of a given policy while making them more insensitive, i.e. certain, no matter how various uncertainties play out. The goal is thus to increase the certainty about the expected outcomes across many plausible scenarios. More formally, this means that there is an expected value and dispersion around this value. In this chapter, in case of maximizing, we define robustness as the mean divided by the standard deviation. The higher the mean, the higher the metric. The smaller the standard deviation, the higher the metric. This will not work in case of minimizing, so there we use the mean multiplied by the standard deviation. The lower the mean, the lower the metric. The lower the standard deviation, the lower the metric. In order to calculate such a robustness metric, each candidate needs to be evaluated using many simulations.

Combining the foregoing description of the outcomes of interest and the decision space, we get the multi-objective optimization problem shown in Equation 3. We have three objective functions. The first two are to be maximized and the third one is to be minimized. The objective function f_i shows how the robustness metrics are calculated. For these functions, a correction factor of 1 is added to the means and standard deviations to prevent division by zero. l_p is the decision space and consists of the triggers specified in Table 15. The set of constraints in Equation 3 shows the boundaries within which the triggers will be optimized.

$$\textit{maximize} \qquad F(l_{p}) = \left(f_{frac}, f_{carbon}, -f_{costs}\right)$$

$$\textit{where} \qquad l_p = \begin{bmatrix} p_{df} \\ p_{ad} \\ p_{sf} \\ p_{sd} \\ p_{pr} \\ p_{dcf} \\ p_{fth} \\ p_{tr} \end{bmatrix}$$

$$f_{frac}(y_{frac}) = \frac{(\mu_{frac}+1)}{(\sigma_{frac}+1)}$$

$$f_{carbon}(y_{carbon}) = \frac{(\mu_{carbon}+1)}{(\sigma_{carbon}+1)}$$

$$f_{costs}(y_{costs}) = (\mu_{costs}+1) * (\sigma_{costs}+1)$$

$$\textbf{subject to} \qquad \begin{aligned} c_{df}&: \quad 0.5 \le p_{df} \le 1.0 \\ c_{ad}&: \quad 0.0 \le p_{ad} \le 0.75 \\ c_{sf}&: \quad 0.0 \le p_{sf} \le 0.5 \\ c_{sd}&: \quad 0.0 \le p_{sd} \le 20.0 \\ c_{pr}&: \quad 1.0 \le p_{pr} \le 2.0 \\ c_{dcf}&: \quad 0.0 \le p_{dcf} \le 0.5 \\ c_{fth}&: \quad 10.0 \le p_{fth} \le 40.0 \\ c_{tr}&: \quad 0.0 \le p_{tr} \le 1.0 \end{aligned}$$

Equation 3: The mathematical formulation of multi-objective optimization

The robustness metric is calculated over a series of computational experiments. Choosing the number of experiments is important and requires trading off computational time and accuracy. To this purpose, a stability check is performed to have a better understanding of the appropriate number of experiments to be used. Figure 15 shows the robustness scores for the three objectives as a function of the number of computational experiments over which the scores are calculated. Again, these computational experiments are generated by sampling across the 46 different uncertainties (see Table 14). As can be seen, after around 500 experiments, the robustness score stabilizes for all objectives. This means that using more than 500 experiments does not add value to the optimization. Thus, for each candidate solution during the optimization, we calculate the mean and the standard deviation for the robustness scores for three objectives over 500 different experiments.

In this study, we use the System Dynamics model for the computational experiments. Each computational experiment specifies a single simulation with this model. The robustness scores f_i

are calculated over 500 experiments. These 500 experiments cover the space spanned by the 46 different uncertainties (see Table 14) and are generated using Latin Hypercube Sampling (Pilger, Costa et al. 2005). This means that for a single evaluation of the objective function, the simulation model is run 500 times.

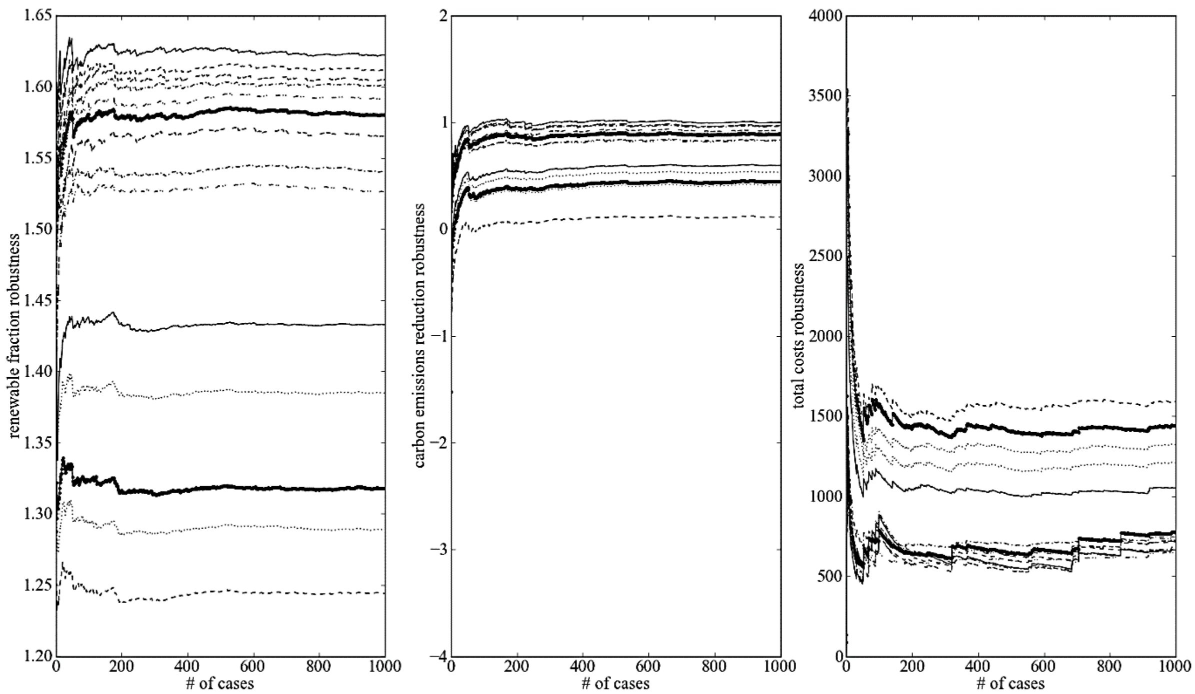

Figure 15: Robustness Check

In this study, we use a real-coded NSGA-II because the triggers have real values. The triggers form the chromosomes, where each chromosome represents a policy setting. We use a binary tournament selection operator in combination with a crowded-comparison operator for the selection criterion (Deb, Pratap et al. 2002). This crowding distance mechanism preserves diversity among non-dominated solutions. The genetic operators used are binary simulated crossover and polynomial bounded mutation (Deb and Agrawal 1995). The NSGA-II algorithm is executed for a pre-defined number of 80 generations with a population size of 200, crossover rate of 0.8 and mutation rate of 0.05. To check convergence, Figure 16 shows the number of additions as a solid line and removals as a dashed line to an archive of Pareto front solutions. As can be seen, the additions are almost stabilized and not many new solutions are being included in the Pareto front from the 65th generation on. Although the removals also seem to be stabilizing, around the 65th generation, there is a big number of removals from the Pareto front. However, the total number of changes to the Pareto front does not fluctuate dramatically for the last 15 generations.

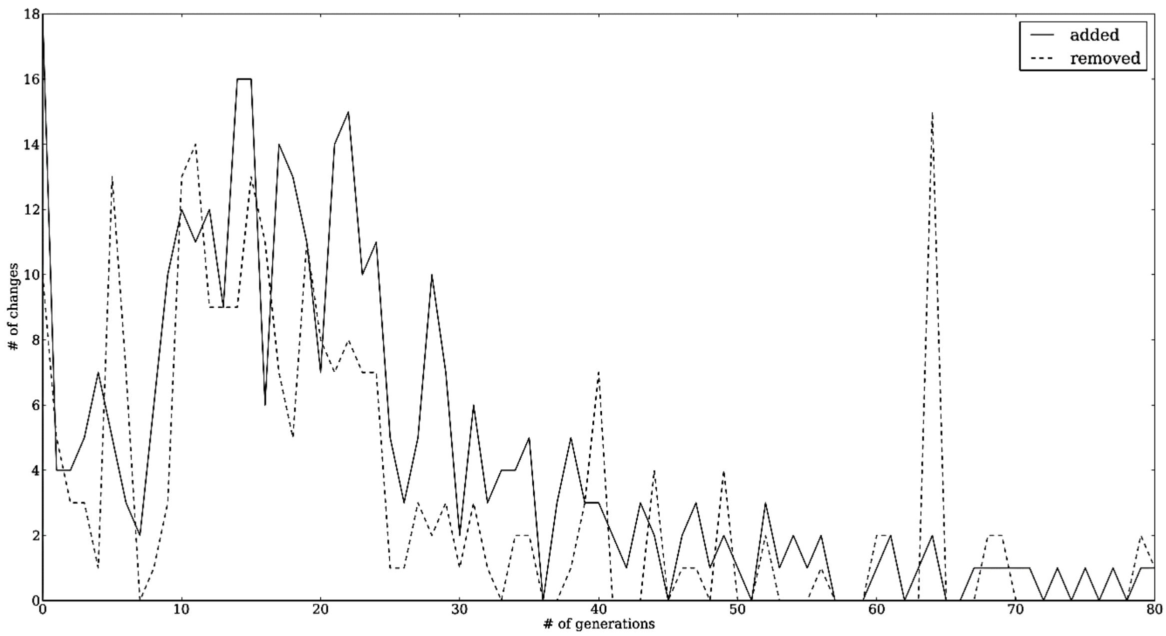

Figure 16: Changes to the Pareto front over the generations

Figure 17 shows a 3D representation of the robustness scores of the three objectives that are normalized between 0 and 1. The gray dots represent the dominated non-Pareto solutions and the black ones the solutions on the Pareto front, which is composed of 98 Pareto solutions. It can be observed how the optimization algorithm has evolved from the initial non-pareto solutions toward a Pareto front by following the gray dots converging to the black dots in Figure 17. As expected, the trade-off between the renewables and emissions objectives and the cost objective can be seen from these results.

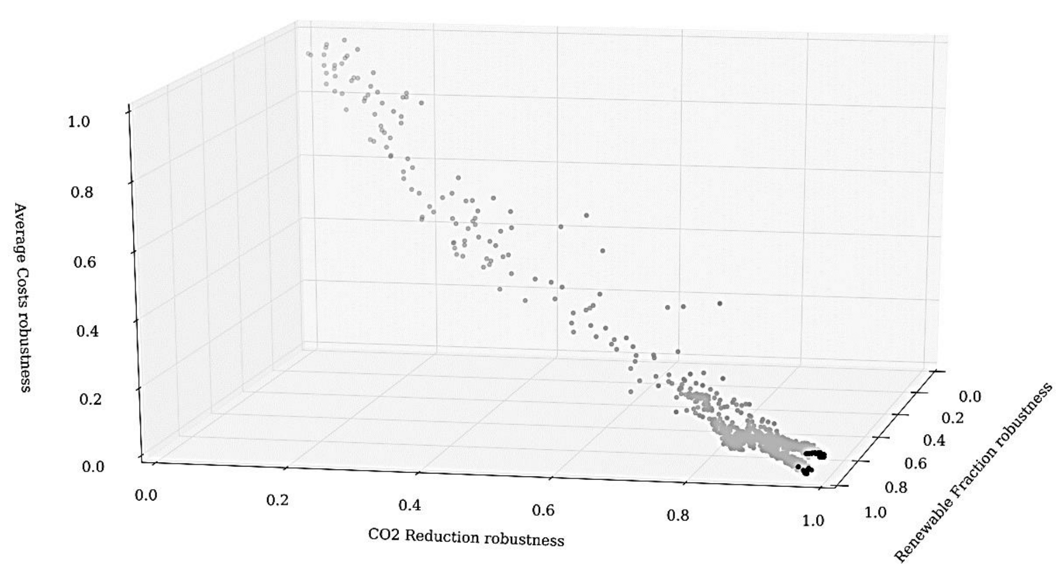

Figure 17: Non-Pareto solutions in gray and Pareto front in black (normalized btw. 0-1)

The Pareto solutions in Figure 17 show that there are two clusters of solutions. In order to have a better understanding of these clusters of solutions, we looked at the robustness scores of the Pareto front solutions and illustrated them by using a parallel coordinates plot in Figure 18. The original robustness scores are scaled between 0 and 1 in order to visualize multiple axes with different scales together. It can be seen that the scores for the average costs form clusters around two points, whereas the renewables fraction is more distributed but still with two clusters, and CO_2 reduction is distributed more evenly. Hence, this suggests that there is a clear and distinct trade-off between renewable fraction and the average costs. If lower average costs are desired, then the trade-off will be lower renewable fraction. However, it is difficult to interpret the CO_2 reduction as it is dispersed among the normalized scores. It should be noted that each line in this figure represent one of the 98 Pareto solutions that have same robustness score. Therefore, regardless of the selection of a solution from the Pareto set, the robustness score will be the same. This figure helps to understand the trade-off relation between the outcomes of interest included in the objective function, but it is not useful to understand by which combination of triggers the Pareto solutions are identified.

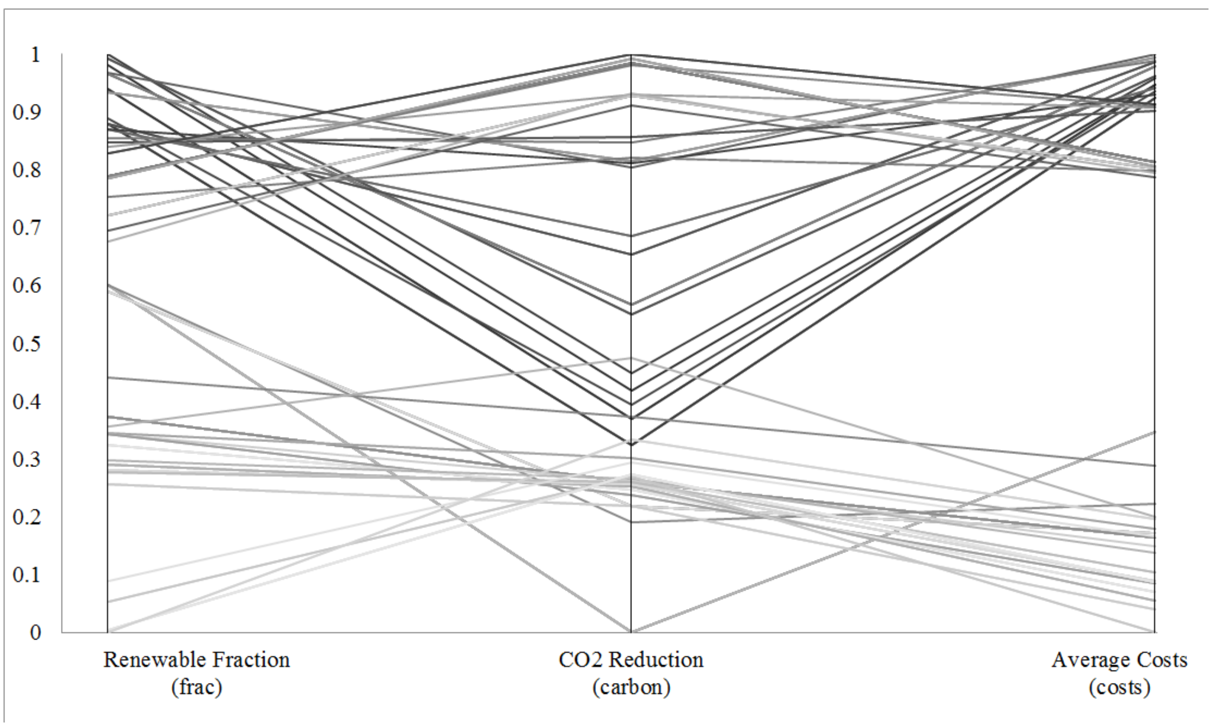

Figure 18: The scores for the solutions in the Pareto approximate set, visualized on a parallel coordinates plot

For a better understanding of how the different solutions on the Pareto front are composed of, it is useful to visualize the values for the decision levers. Figure 19 shows this in a parallel coordinates plot. The trigger values are normalized between 0 and 1 due to the scaling issue of different ranges for each trigger. The parallel coordinates in Figure 19 show that the desired fraction (*df*), the forecast time horizon (*fth*), the decommissioning factor (*dcf*), and the subsidy duration (*sd*) are the binding constraints. In order to achieve the Pareto front, the desired fraction needs to be set to its maximum, the forecast for the renewable fraction should be restricted to a maximum of 12 years ahead, the decommissioning factor of Action 2 should be larger than 50% and the subsidy duration should at least lie between 18 and 20 years.

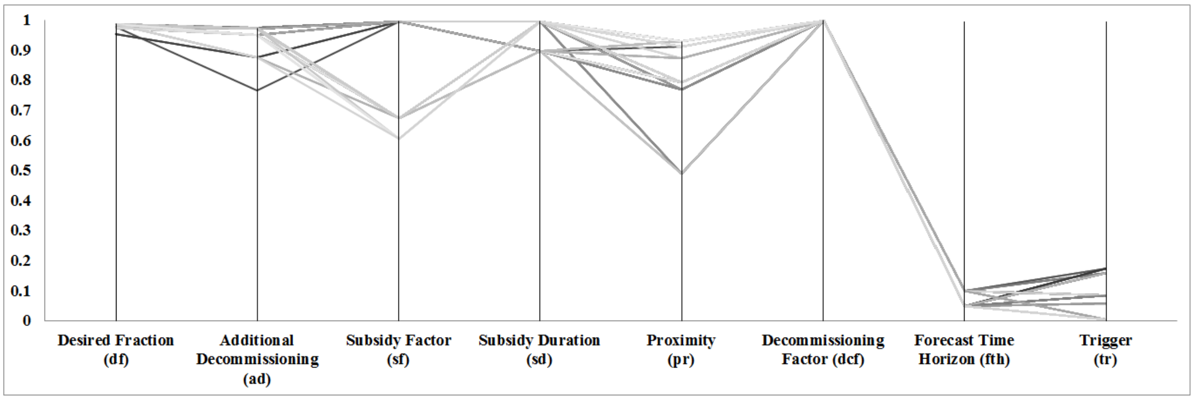

Figure 19: The values of the decision levers for the solutions in the Pareto approximate set, visualized on a parallel coordinates plot

4.4. Conclusions

In recent years, there has been an increasing interest in adaptive policies. These policies are designed from the outset to be adapted over time in response to learning and new information. The efficacy of adaptive policies hinges on identifying appropriate conditions, or triggers, for adapting the policy. Here, one has to find a balance between adapting a policy too early or too late. Up until now, the literature on adaptive policies used best guesses and historic data in specifying these conditions. Given the importance of appropriate trigger for the efficacy of an adaptive policy, there is a need for a method for supporting the identification of appropriate triggers. In this chapter, we have argued and demonstrated that robust multi-objective optimization is a method for this. By focusing on robustness, the presence of uncertainty is explicitly accounted for. By using a multi-objective optimization approach, the multiplicity of outcomes of interest intrinsic to multi-stakeholder decision problems is addressed. The outlined approach helps in identifying multiple alternative policies, instead of producing a single "best" policy. Thus, it creates room for a better-informed policy debate on trade-offs.

We demonstrated the efficacy of multi-objective robust optimization for specifying trigger values in a case study on improving the current ETS policy of the European Union. It is clear that there is a need for more innovative policies than the current ETS policy to promote the transition toward a sustainable system. We developed a basic adaptive policy using educated guesses for the different triggers. Although this adaptive policy outperformed the ETS policy, we then showed it is possible to improve the performance of this adaptive policy even further through multi-objective robust optimization. Figure 20 shows a comparison of the adaptive policy and three solutions randomly chosen from the Pareto front identified by the multi-objective robust optimization. The solid line represents the basic adaptive policy and the dashed lines represent the three optimized policies. The results indicate that the proposed approach can be efficiently used for developing policy suggestions and for improving decision support to policymakers in energy policy. By extension, it is possible to apply this methodology in dynamically complex and deeply uncertain systems such as public health, financial systems, transportation, water resources management, climate adaptation, and housing.

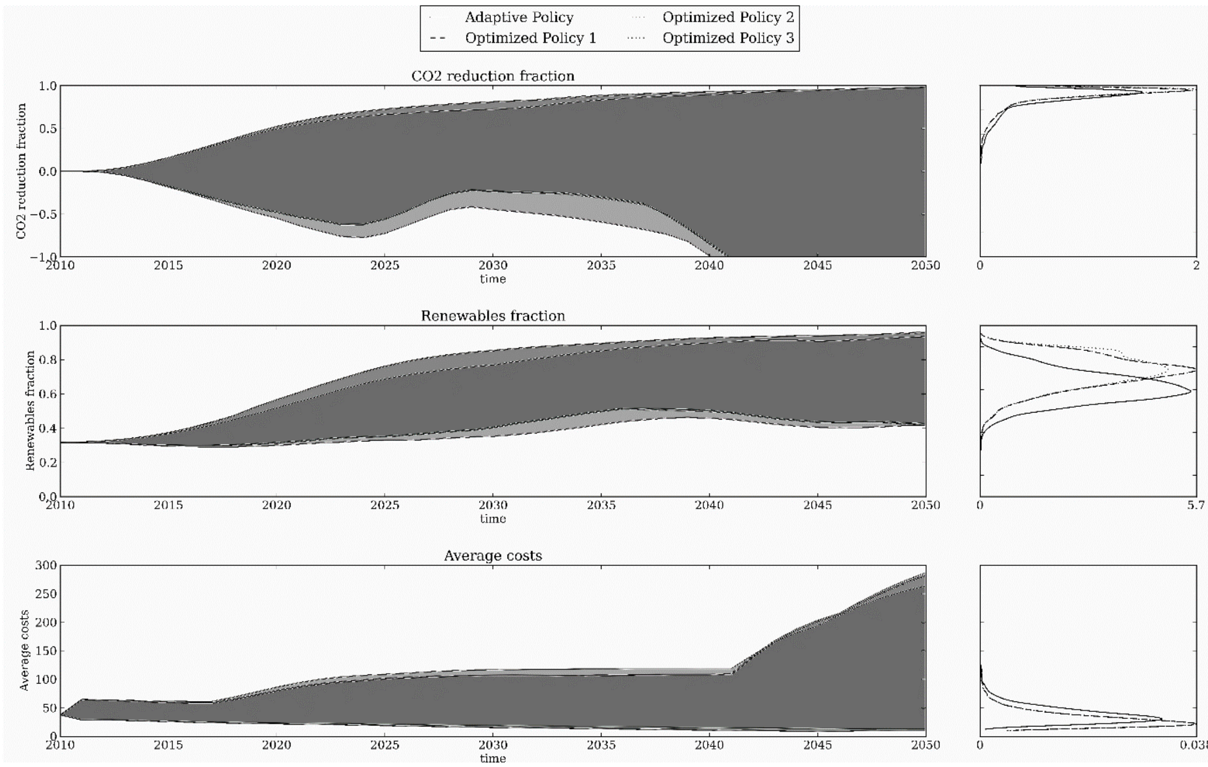

Figure 20: Comparison of the adaptive and three optimized policies from the Pareto front

The choice of robustness metric has an important influence on the Pareto solutions identified. In this study, we have used a robustness metric based on the mean divided by the standard deviation for maximization, and the mean multiplied by the standard deviation for minimization. It is plausible that if a different robustness metric had been used, the resulting trigger values would be substantially different. For instance, a regret based metric (Lempert and Collins 2007) can lead to different results. However, our work does not hinge on the particular robustness metric. Still, further work is needed to compare and contrast alternative robustness metrics, in pursuit of guidance on the selection of robustness metrics appropriate to the specific decision problem at hand.

Multi-objective optimization and robust optimization in isolation are already computationally intensive. Combining the two makes this even worse. Computational constraints may therefore limit the scope of the analysis. However, sometimes quick analysis is essential, for instance, if the time window for making a decision is very short. For such conditions, it might be better to take advantage of faster and quicker techniques such as Multi-Criteria Decision Analysis (Belton and Stewart 2002, Figueira, Greco et al. 2005). Another consequence of the time consuming nature of the outlined approach is that it becomes necessary to work with relatively small, less detailed models. This is motivated by the fact that it is better to be roughly right, than precisely wrong. In this chapter, we used a System Dynamics model. Although such models are often focused on the general dynamics over time, rather than exact values, there has been some work on coupling these models to optimization algorithms for a variety of purposes including model testing (Miller 1998, Oliva 2003, Yücel and Barlas 2011), model calibration (Oliva 2003, Yücel and Barlas 2011), and, most notably in this context, policy design (Coyle 1985, Yücel and Barlas 2011, Kwakkel and Pruyt 2013).

In this chapter, we used NSGA-II for solving the multi-objective optimization problem. Although it is one of the best-known algorithms, NSGA-II can perform poorly in particular classes of problems (Reed, Hadka et al. 2013). The approach that we have presented in this chapter does not necessarily rely on NSGA-II. Other more modern algorithms can be used instead of NSGA-II and might even have better performance characteristics. For example ε-NSGA-II, an extension to NSGA-II, combines ε-dominance archiving with adaptive population sizing, and time continuation, which prevents deterioration in the Pareto approximate set while maintaining diversity (Goldberg 2002, Kollat and Reed 2006). Even more sophisticated and of potential relevance are auto-adaptive algorithms such as Borg (Hadka and Reed 2013) which tailor the various optimization parameters and evolutionary operators to the specific problem(Hadka and Reed 2013, Reed, Hadka et al. 2013). Future work is needed to investigate the potential of these more recent and more sophisticated algorithms to supporting the robust adaptive design approach.

The proposed approach in this study does not aim to replace decision makers but aims to provide a better guided decision-making process. The Adaptive Robust Design approach, which combines RDM with an explicit framework for designing adaptive policies (Hamarat, Kwakkel et al. 2013, Walker, Haasnoot et al. 2013), together with multi-objective robust optimization helps to design robust adaptive policies in the presence of uncertainty and a multiplicity of objectives. The identification of the Pareto front provides the decision maker with a multiplicity of choices and makes the trade-offs between these choices transparent. As such it can be used to facilitate a process of deliberation with analysis (National Research Council 2009).

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The previous chapter has illustrated how the multi-objective robust optimization approach helps policymaking answering the problem of multiple conflicting objectives. Three different objectives have been optimized by fine-tuning the triggers that are used for designing adaptive policies. This has been the final part of the research that has been conducted during this study.

Now, we will close this thesis with the conclusions and discussions chapter. We will summarize what has been done throughout this study and will provide the answers for the key research questions. A review of the important research topics will be shown and it will be followed up by a future research agenda.

Chapter 5 - Conclusions, Discussion and Reflection

5.1. Brief integrated summary

Each piece of scientific research is a small contribution to the overall scientific knowledge. Science builds on itself by constructing scientific knowledge based on what is available and then paving a way to new knowledge. For instance, we have used the Adaptive Policymaking framework, which was available, to develop a new approach named Adaptive Robust Design. The initial step of scientific method is to make observations and ask questions where there are no answers yet. To make a *small* contribution for our common scientific knowledge, we have formulated a research objective to be addressed. The objective of this study was to ***improve the analytical support for model-based policymaking in order to handle deep uncertainty better***. As this research objective can be difficult to address in a single step, it is logical to break the main question into sub questions. Therefore, we have formulated our research direction through three distinct but strongly interrelated sub questions. Addressing these sub questions has contributed to the research objective of this thesis.

In order to introduce the current practice in analytical support for model-based policymaking under deep uncertainty, the introduction chapter opened the stage by illustrating the recent developments. Several approaches such as Info-Gap Theory, Real Options analysis, Adaptive Policymaking approach, Robust Decision Making, Dynamic Adaptive Policy Pathways and Many-Objective Robust Decision Making, and Exploratory Modeling and Analysis are explained. We note that different approaches have different limitations for supporting policymaking under uncertainty. Info-Gap theory focuses only on parametric uncertainties and Real Options analysis assesses the value of options based on associated probabilities. These approaches provide limited support for policymaking in the existence of deep uncertainty. Another approach, RDM, explores only the *vulnerabilities*, instead of also exploring *opportunities* for which ranges of uncertainties the candidate policy can perform better to exploit such opportunities. Furthermore, the RDM approach lacks adaptivity due to a lack of guidance on explicitly considering the dynamic adaptation of the plan over time which results in a robust but static strategy. We also point out the importance of using advanced data analysis techniques that are not but can be utilized in combination with model-based policy design. Although some approaches, such as RDM, use machine learning algorithms, a clearly structured approach to integrate advanced analysis techniques into analytical support for model-based policymaking is required. Another important issue in model-based policymaking is how to address the multiple conflicting objectives of multiple stakeholders involved. A possible solution can be to use multi-objective optimization in combination with robustness considerations.

5.1.1. Answers to key research questions

Following the introduction, the next key research topic was **the utilization of advanced data analysis techniques to deal with deep uncertainty in policymaking support**. This question has been addressed in Chapter 2, which illustrates the use of Exploratory Modeling and Analysis in dynamic policy design in combination with advanced analytical techniques. EMA is a methodology that uses mathematical models for analyzing dynamically complex issues under uncertainty. As a case, we have used simple System Dynamics models about energy transitions to explore a wide range of deep uncertainties on parameters, model structures and so on. To answer the key research question on the utilization of the analytical tools, we have focused on developing dynamic policies by using various analytical methods/techniques such as feature scoring, CART and PRIM. We used feature scoring to identify the importance ranking of the uncertainties in terms of their impact on the end state of the fraction of renewable technologies. Furthermore, CART and PRIM analysis helped to have a better understanding of which combination of uncertainties lead to (un)favorable outcome spaces. Using the findings of these techniques, the policy design has been iteratively improved. Chapter 2 shows that using analytical techniques such as feature scoring, CART and PRIM together with EMA can help improve analytical support for policymaking deep under uncertainty.

The most important research question, which forms the foundation of the main objective of this thesis, was **how to operationalize the Adaptive Policymaking framework**. The Adaptive Policymaking framework was proposed by Walker et al. (Walker, Rahman, & Cave, Adaptive policies, policy analysis, and policy-making, 2001) and extended by Kwakkel et al. (2010) and illustrates a stepwise approach for developing adaptive policies. As also stated by the authors, there was a need for the operationalization of this framework and further development of adaptive and robust tools and methods. Therefore, we have proposed an iterative model-based approach for developing adaptive policies under uncertainty and we have called this approach Adaptive Robust Design (ARD). The iterative approach that utilizes EMA for designing robust adaptive policies helps to identify and address both vulnerabilities and opportunities, resulting in a robust adaptive policy. The main steps of Adaptive Policymaking framework such as assembling a basic policy, identifying vulnerabilities and opportunities, and contingency planning have been included in the ARD approach along the lines of the EMA methodology. The proposed Adaptive Robust Design approach has been a contribution for improving policymaking under uncertainty as illustrated by the citations that can be found on this article (Hamarat, Kwakkel, & Pruyt, 2013). ARD has been referenced for being a valuable approach for designing adaptive policies, using robust optimization in adaptive policymaking and for the use of triggers and signposts to ensure adaptivity (Kwakkel, Haasnoot, & Walker, 2016; Kwakkel, Haasnoot, & Walker, 2016; Bhave, Conway, Dessai, & Stainforth, 2016; Werners, et al., 2013). For instance, Eker & van Daalen (2015) have followed our ARD approach for solving robust optimization problem. Additionally, Kwakkel et al. (2015) has pointed our ARD approach as one of the important reference source for the basis of the Dynamic Adaptive Policy Pathways (DAPP) approach that is developed by Haasnoot et al. (2013). This approach combines Adaptive Policymaking and Adaptation Pathways (Haasnoot, Middelkoop, Offermans, Van Beek, & Van Deursen, 2012) into an integrated stepwise method, which supports policymaking under uncertainty. The fundamental concept of Adaptation Pathways are the adaptation tipping points, which determine the points to take new actions to achieve objectives. This concept has strong similarities with using triggers and signposts in our ARD approach. An adaptation tipping point occurs when a particular action is not adequate anymore and a new action should be taken, whereas a trigger in our approach specifies the conditions that require to take a pre-specified action to change the plan.

As a follow-up question, we have asked what can be done **for supporting adaptive policymaking in the presence of multiple conflicting objectives**. Different valuation of outcomes by different stakeholders is one of the characteristics of deep uncertainty. To support adaptive policymaking under deep uncertainty, the situations that involve multiple objectives need also to be addressed. In general, optimization methods tackle a single objective or multiple objectives merged into a single one. However, policymaking issues under deep uncertainty often include multiple and possibly conflicting objectives, which are difficult to combine as one. To this purpose, we have developed an approach to use multi-objective robust optimization in the context of adaptive policymaking. The triggers and signposts are essential components of ARD, and these trigger values have been explained and optimized in section 4.2. We used multi-objective robust optimization for finding optimal trigger values. The optimization method that we used combines two different approaches, namely robust optimization and multi-objective optimization. Robust optimization helps to consider the presence of deep uncertainty, and multi-objective optimization helps consider multiple conflicting objectives. Multi-objective robust optimization helps finding a list of Pareto optimal solutions, which do not dominate each other for different combinations of trigger values. That is to say, these different policy designs on the Pareto list are multiple alternative policy designs that policymakers can choose from based on subjective preferences. This approach helps policymakers by eliminating the inferior choices and providing a multiplicity of Pareto-optimal choices.

We have tackled each sub research question step by step to provide answers that will contribute to the main research objective. This thesis concludes that the **Adaptive Robust Design approach in combination with multi-objective robust optimization will improve the support for policymaking under deep uncertainty.**

5.2. Review of the research

The main contribution of this study to the field has been the Adaptive Robust Design approach, which operationalizes the Adaptive Policymaking framework. By illustrative case studies in the previous chapters, it is shown how ARD can be effectively used for developing adaptive robust policies under deep uncertainty. The key contribution has been on the methodological niche. This approach can be applied to any system of interest where mathematical models are available. By following the steps of ARD, it is possible to develop adaptive robust policies. In the scope of this study, we have used small high-level System Dynamics models about the energy transition towards renewables. The first two models used are smaller and more generic in terms of the model structure representations. The last model used is still about the same system of interest but in more detail and provides a better representation of the real world system. Multiple stakeholders with multiple, possibly conflicting, objectives are represented more elaborately in this model. However, since all models are wrong (Sterman, 2002), any single model should not be treated as the "true" representation. Therefore, it is proposed to use an ensemble of models in an exploratory manner to cover an ensemble of futures. In this study, all the mathematical models have been used in an exploratory manner and for illustrative purposes only. Therefore, it should be reminded and emphasized that the focus of this study is more on the methodological contribution than the precise policy designs on energy transitions.

As the key contribution of this study is about the methodological approach, there are some areas where I would like to provide a more in-depth perspective. These are explained below in more detail.

5.2.1. Patient Rule Induction Method (PRIM)

Another important part of the ARD approach was to operationalize the Patient Rule Induction Method (PRIM) to discover subspaces of the multidimensional uncertainty space. PRIM is a data mining technique, which identifies problematic (vulnerabilities) and promising (opportunities) sub-regions in the output space and the regions in the input space that result in these specific regions of the output space. This valuable information helps us translating these subspaces into a combination of specific uncertainty ranges and these combinations can be interpreted as different scenario settings where each uncertainty subspace represent a scenario. Therefore, PRIM is commonly used for scenario discovery in the presence of deep uncertainty (Kwakkel, Auping, & Pruyt, 2013; Kwakkel & Jaxa-Rozen, 2016). Although the aim of PRIM is to identify orthogonal boxes in the input space, this becomes difficult in the presence of nonlinear interactions of uncertainties. Auping (2018) argues that this difficulty is due to two main reasons: nonlinearity and equifinality. It is possible that the specific regions of interest in input space, namely the orthogonal boxes, can be spread among the complete range of uncertainties due to nonlinear interactions. As we also have faced similar problems, we used the enhanced version of PRIM that is proposed by Kwakkel et al. (2013) and called Principal Components Analysis PCA-PRIM. It includes a preprocessing step to transform input parameters of the uncertainty space into a smaller number of clusters of input parameters that still contain the information of the uncertainty space. The version of PCA-PRIM used in this thesis allows rotating clusters of input parameters, instead of uncertain parameters separately. This enhancement of PRIM enables to identify high quality PRIM boxes with higher coverage rates, in other words, improved scenario discovery. We have used this enhanced version in this study, which has been an important part of the ARD approach. It should be noted that the PCA method used can be less effective in terms of transforming the input parameters into clusters for categorical uncertainties. A possible future enhancement can be utilizing PCA together with a categorical PCA (Linting, Meulman, Groenen, & van der Koojj, 2007) to handle categorical uncertainties properly.

5.2.2. Robustness metrics

In Chapter 4, we used an optimization approach, which combines multi-objective optimization and robust optimization. Robust optimization is a method that helps finding optimal outcomes under deep uncertainty where probability distributions of uncertainties are unknown. The quantification of robustness is critically important for robust optimization and this is related to the choice of robustness metric used. In this study, we have used a robustness metric based on the mean divided by the standard deviation for maximization, and the mean multiplied by the standard deviation for minimization. The mean-variance metric is similar to the signal-to-noise ratio used in control theory. This metric is calculated using statistical information (i.e. mean, standard deviation) which is a practical and useful approach. Since using robust optimization together with multi-objective optimization for adaptive policymaking in this study was new and not experimented before, we preferred this practical robustness metric in our analysis. Eker and van Daalen have also utilized this similar signal-to-noise ratio robustness metric in their article on biomethane production in the Netherlands (2015). On the other hand, Kwakkel et al. (2016) used mean and standard deviation separately as they claim that it allows easier interpretation and more decision relevant information. Eker and Kwakkel (2018) used both mean-to-standard deviation together with a metric based on maximum regret but concluded that the results of the analysis were indifferent for the choice of metric. Furthermore, Eker (2016) made an extensive comparison of several robustness metrics from three different approach groups that are expectation based, regret based and statistical measures. Although Eker does not provide a clear comparison of different metrics, she discusses the benefits and shortcomings of different groups of metrics. Assessment of policy performance by using the expectation- based metrics can be considered to have a limited view due its focus on a single aspect of the scenario space. Regret-based metrics are more powerful than statistical measures as regret-based metrics assess each policy in each scenario, whereas statistical metrics measure the impact of a policy over the entire scenario space. Nevertheless, statistical ones can be more preferable over regret-based ones in the existence of an uneven distribution of the scenario space. Obviously, there are many other metrics available to use for quantifying robustness but it is not clear and straightforward how to select the appropriate metric. A detailed categorization and comparison of robustness metrics is done by McPhail, et al. (2018), where they propose a unifying framework. This framework helps determining when and which robustness metrics to use for assessing different decision alternatives by considering different robustness families and preferences of decision maker on risk and robustness. The pairwise comparison of several robustness metrics shows that our mean-variance metric has a high ranking stability with most of other metrics, where "a ranking stability of 100% indicates that the metrics agreed on the rankings for every pair of decision alternatives, while 0% indicates that one metric ranked the decision alternatives in reverse to the other metric" (McPhail, et al., 2018). However, our metric is criticised as mean and variance combination is not always monotonically increasing and good and bad deviations are treated equally. As a future research, it can be interesting to try different robustness metrics such as minimax, maximin or Huurwicz with our Adaptive Robust Design approach for a comparative analysis.

5.2.3. Multi-objective optimization

Policymaking issues generally involve multiple stakeholders where each has its own objective to achieve. In the presence of multiple objectives, a common approach is to attempt to combine these objectives into a single objective if possible. A possible solution is to give weights to each objective and create a single weighted objective. However, it is often not clear how to assign proper weights to objectives, especially in the presence of complexity, deep uncertainty and multiple stakeholders. It might be problematic that different stakeholder preferences may not be considered properly. Different weights may lead to different optimal solutions for which one objective dominates another one. Therefore, a possible approach can be to provide a set of solutions where no solution dominates others and such non-dominated solutions are called Pareto optimal solutions. Multi-objective optimization helps dealing with multiplicity of conflicting objectives by finding Pareto optimal solutions. To make use of this competence, we utilized multi-objective optimization together with the ARD approach to deal with multiple conflicting objectives. In the light of the combination of ARD and multi-objective robust optimization in Chapter 4, Kwakkel et al. (2015) have also applied multi-objective robust optimization together with DAPP. By using this combined method, a set of robust candidate pathways can be identified in the presence of deep uncertainty.

For communicating the results of the multi-objective robust optimization clearly, we have used parallel coordinate plots for visualizing the Pareto front solutions. This visualization technique is used for multivariate and numerical data to illustrate the relationships between the variables. This helped us to see whether there are clusters of scores for different objectives. Furthermore, we visualized eight trigger values of the different solutions on the Pareto front to see the relationships between these triggers. This technique enabled us to identify which set of trigger values characterizes the Pareto front solutions.

Evolutionary algorithms, which are inspired by biological evolution and population dynamics, are well suited for multi-objective optimization problems. Therefore, we used the NSGA-II algorithm (Deb, Pratap et al. 2002) which is one of the most efficient algorithms. This multi-objective evolutionary algorithm generates a population of candidate policy settings, defined by different combinations of trigger values. Iteratively, the algorithm aims to identify a population for which candidate policy settings are on the Pareto front. As our approach in this study is not specifically dependent on the NSGA-II algorithm, it is also possible to utilize other algorithms if performing better. An example is ε-NSGA-II, an extension to NSGA-II, which has new capabilities such as adaptive population sizing and time continuation (Goldberg 2002, Kollat and Reed 2006). In parallel to this study, Kasprzyk et al. (Kasprzyk, Nataraj, Reed, & Lempert, 2013) utilized this extended version of NSGA-II in their many-objective robust decision-making research. More complex algorithms are auto-adaptive algorithms such as Borg, which tailor the various optimization parameters, and evolutionary operators to the specific problem (Hadka and Reed 2013, Reed, Hadka et al. 2013) (Trindade, Reed, Herman, Zeff, & Characklis, 2017; Jaxa-Rozen, Bloemendal, Rostampour, & Kwakkel, 2016). The usage of evolutionary algorithms clearly shows that they have significant potential in supporting complex and uncertain policy analysis problems, which is also stated in the position paper of Maier et al. (2014).

5.2.4. Limitations of the research

This study provides a methodological approach towards the research objective of how to improve model-based policymaking support under deep uncertainty. We have proposed an approach for designing adaptive robust policies, and furthermore to be used in combination with multi-objective robust optimization techniques. To illustrate the performance of the proposed approach we have used mathematical, specifically System Dynamics (SD), models in which the dynamics of energy transitions are explored. As the focus of this study is primarily on the methodological development, the models used in this study are small but exploratory models, which are not very detailed, and at an aggregated level that still captures the main dynamics of system of interest.

5.3. Reflection on the relevance for real-life policy issues

This study focuses on the methodological development of analytical support for policymaking under uncertainty. To that purpose, we have used relatively simple and generic models for analysis purposes to illustrate the performance of the proposed methodology of this study. Beside the methodological focus, we reflect here on several relevant aspects that relate to application of the methodology in real-life policy settings.

An important consideration point is the computational cost of using the proposed approaches in real-life studies for policymaking support. Simple and generic models can still be useful for a fast explorative high-level analysis. However, for analysis purposes of complex real-life cases, utilization of comprehensive models with detailed specifications will be required to design real-life policies. As the proposed approach in this study necessitates extensive computational power, it can be very costly to use this approach for a system of interest with complex models. However, with advancing computational power, this methodological approach can also support real-life cases such as energy policymaking, health policy development, migration issues, and water management.

Another issue to point out is that model-based policy analysis brings already a significant level of complexity to be grasped by policymakers. It does not make much sense to try to explain the advanced analytical approaches to policy makers. If however this advanced model-based analysis is seen as a black box, it is possible that the policymakers may have a lack of trust in such approaches and their results. Therefore, analysts should make serious efforts to explain the rationale of their findings in a clear and comprehensible way to policy makers. And this will require to establish communication methods to funnel complex results into simple and clear stories. To this purpose, advanced visualization techniques (e.g. parallel coordinate plot, high-dimensional bubble chart, heatmap, etc.) can help analysts prepare a clear-cut story.

Adaptive policymaking has been applied to real-life situations when confronted with uncertainties. For example, the pension age in the Netherlands after 2022 will be adapted based on the average life expectancy (CBS Statistics Netherlands, 2014). As there is uncertainty on the average life expectancy, developing a static policy on the pension age possibly requires to revise the pension age policy frequently. A policy that adapts based on the average life expectancy can help tackling deep uncertainty. This is a clear example of how adaptive policymaking can be implemented for designing adaptive policies in real-life. There are also other recent examples where adaptive policymaking is applied in different areas: For example, Jittrapirom et al. (2018) applied adaptive policymaking for implementing Mobility-as-a-Service (MaaS), an innovative transport concept that combines a range of transport modes and services to provide a user-orientated service via a single interface, for the city of Nijmegen. The authors show that adaptive policymaking addresses uncertainty by incorporating adaptation as part of the process and provides alternative transport planning methods different than the traditional approaches. Another similar example is the potential future use of automated taxis (AT) in a city that is confronted with deep uncertainty about the implementation of these ATs (Walker & Marchau, 2017). The authors apply the dynamic adaptive policymaking approach and illustrate that "compared to traditional policymaking, the adaptive approach is highly promising in terms of handling the range of uncertainties related to AT implementation. Dynamic Adaptive Policy Pathways, an elaboration of adaptive policymaking, is implemented in a simulation game environment for a real-life case of flood risk management in New Zealand (Lawrence & Haasnoot, 2017). The 'safe' simulation game environment showed that adaptive pathways planning for climate change adaptation can be adopted under conditions of deep uncertainty.

Multi-objective robust optimization provides a set of non-dominated solutions, namely the Pareto front, by eliminating dominated solutions gradually. Although the Pareto front offers multiple options to select from, it can nevertheless be perceived as too narrow by the policymakers. Policy makers may wish to take other considerations into account than those included in the model-based analysis. . Therefore, it is important to communicate with the policymakers that this proposed approach is a guide for them to help making informed decisions, but not a substitute that chooses the *best* policy option for a system, in place of the policymakers who usually seek a feasible satisfying option.

5.4. Future research agenda

This thesis has proposed an answer for ***improving support for model-based policymaking to better handle deep uncertainty*** by providing a new methodological approach. Starting from a pragmatic approach, we have developed a systematic approach for designing adaptive policies under uncertainty. Furthermore, we have combined complex optimization techniques with the adaptive robust design approach. There are however many new challenges available for the future of the field.

One of the future research areas is about ***exploring deep structural uncertainty of models of the system of interest***. The adaptive policymaking studies using exploratory modeling have, so far, predominantly focused on the uncertainty exploration of model parameters or model structures. Commonly, a model of the system of interest is built which incorporates the parametric and structural uncertainties. This model is significantly dependent on the modeller's mental model, which can be defined as the conceptual representation of the perceived structure of the system (Kwakkel & Pruyt, 2015). This means that one model represents one perception of the system of interest, whereas it is known that multiple different perceptions can be applicable, especially under deep uncertainty. Therefore, there is an evident need to consider exploring uncertainty caused by multiple perspectives leading to multiple models (Auping, Pruyt, & Kwakkel, 2014). Initial attempts for exploring multiple models have been made by researchers (Pruyt & Kwakkel, 2014) (Auping, Pruyt, & Kwakkel, 2014), which needs to be further investigated. Recently, Auping (2018) has proposed an enhanced model development cycle to incorporate multiple conceptual and simulation models for exploratory modeling practices. Considering uncertainty in early stages of model development can help developing multiple models, instead of using a single consolidative model in an exploratory manner. Furthermore, Pruyt et al. (2018) recently developed a new modeling technique that allows developing multi-layered/multi-scale System Dynamics models by implementing spatial concepts. This innovative technique can help easily build advanced models that consider complex geospatial interactions for cases where policymaking is extremely difficult such as global migration dynamics (Wigman, 2018). ***Using this multi-layered SD modeling approach in combination with ARD approach can be a future research topic, which will help improve policymaking support for challenging issues involving complex geospatial interactions***. A possible central issue will be the limitation of the computational capacity that can handle the extensive number of model elements. For instance, when the detail level of multi-layered SD model of global migration dynamics is on the city level, the number of possible migration flows between 50000 cities will be approximately 2.5 billion. As the number of model elements can grow exponentially, the added value of the additional detail level should be evaluated in comparison to the added computational complexity (Wigman, 2018).

The ARD approach requires the use of mathematical models in an explorative manner, which is computationally very intensive. Moreover, we combine ARD with multi-objective and robust optimization techniques that make computation even more exhaustive. Hence, it is certainly crucial that the computational support for this research field should be extensive and efficient. In this study, we have used a workbench developed in Python language, which allows for generating explorative experiments, analysis of outcomes and visualization. This workbench is called the Exploratory Modeling Workbench and it is publicly available (Kwakkel J. H., 2017). Another similar framework is the open source framework focused on many objective robust decision-making, which is called OpenMORDM (Hadka, Herman, Reed, & Keller, 2015). This framework is developed in R language, which is another popular programming language, and provides analysts a platform for planning under deep uncertainty. Both the workbench and the platform are publicly available and more importantly, they are open source. The computational coding support, such as using Python or R, of such platforms is significant to provide necessary technical resources for analysts to operationalize the theoretical approaches. Such coding support will provide accessibility and quick implementation of analytical support. ***Therefore, there should be more open source platforms that provide advanced analytical support for policymaking under deep uncertainty studies.*** Increasing the collaboration among researchers plays an essential role and this can be done by establishing new societies of multi-disciplinary researchers, such as the DMDU Society (DMDU Society, 2018) that is a group of people working on improving decision-making under deep uncertainty.

As a summary of a possible future research agenda, one important direction can be to use more complex models for policymaking support in combination with the ARD approach. For building complex models, the enhanced model development cycle by Auping (2018) or the advanced multi-layered SD model building technique by Pruyt (2018) can be used. However, using complex models with the ARD approach will be computationally more intensive. Therefore, computational coding support for advanced analysis should be improved in the future. A possible direction is to *go out and explore* openly the useful analytical techniques from different fields to be used for policymaking under uncertainty. This open exploration can be facilitated by establishing new societies of multi-disciplinary researchers to empower collaboration. Exploration of new techniques and collaboration with multi-disciplinary researchers will result in an inventory of new analytical techniques that can be used to develop new methods/approaches. Recently, a taxonomy of analytical tools and approaches for supporting decision making under deep uncertainty has been proposed (Kwakkel & Haasnoot, 2019) that "analysts can use the taxonomy for designing context-specific approaches to support decision making under deep uncertainty". In addition to the variety of existing approaches, this list of new methods/approaches should be categorized according to which method or technique is more suitable for the problem of interest. Such a categorization can be used as a guidebook for policy analysts to help select methods and techniques when faced with different policy problems. Furthermore, this guidebook categorization can provide advanced assistance for policy analysts and avoid potential miscommunication between analysts and policymakers by creating transparency on methods used by policy analysts. This need for further guidance on when and how to apply a specific DMDU approach has been also put forward by (Marchau, Walker, Bloemen, & Popper, 2019) as one of the challenges of DMDU society.

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Appendix A. Python Scripts

In this thesis, we have conducted a large set of computational experiments and applied various analytical techniques for the analysis required in the main body chapters, respectively the chapters 2, 3 and 4. For this purpose, we have used the Exploratory Modeling Workbench (Kwakkel J. H., 2017), which is implemented in Python language. Further details of the workbench can be accessed from this website. https://emaworkbench.readthedocs.io/en/latest

Reference: Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, 239-250.

In this appendix, the Python scripts that are used in the chapters 2, 3 and 4 are provided.

Chapter 2:

5000 simulations without policy, static policy and dynamic policy

```
from __future__ import division
from ema_workbench.em_framework import (ModelEnsemble, RealParameter,
                                        TimeSeriesOutcome, ScalarOutcome, Outcome)
from ema_workbench.em_framework.parameters import Policy, IntegerParameter, CategoricalParameter
from ema_workbench.util import ema_logging, save_results
from ema_workbench.connectors.vensim import VensimModel

if __name__ == '__main__':
    ema_logging.log_to_stderr(ema_logging.INFO)
    model = VensimModel("FTA", wd="D:\Workspace\EMA_workbench\src\FTA_Ch2\models",
                        model_file = "ESDMAElecTrans_NoPolicy.vpm")
    model.outcomes = [TimeSeriesOutcome('total fraction new technologies'),
                      TimeSeriesOutcome('total capacity installed')]
    #Plain Parametric Uncertainties
    model.uncertainties = [
        RealParameter("ini cap T1", 14000,16000),
        RealParameter("ini cap T2", 1,2),
        RealParameter("ini cap T3", 1,2),
        RealParameter("ini cap T4", 1,2),
        RealParameter("ini cost T1",500000,1500000),
        RealParameter("ini cost T2",5000000,10000000),
        RealParameter("ini cost T3",5000000,10000000),
        RealParameter("ini cost T4",5000000,10000000),
        RealParameter("ini cum decom cap T1",5000000,10000000),
        RealParameter("ini cum decom cap T2", 1,100),
        RealParameter("ini cum decom cap T3", 1,100),
        RealParameter("ini cum decom cap T4", 1,100),
        RealParameter("average planning and construction period T1",1,5),
        RealParameter("average planning and construction period T2",1,5),
        RealParameter("average planning and construction period T3",1,5),
        RealParameter("average planning and construction period T4",1,5),
        RealParameter("ini PR T1", 0.85,0.95),
        RealParameter("ini PR T2", 0.7,0.95),
        RealParameter("ini PR T3", 0.7,0.95),
        RealParameter("ini PR T4", 0.7,0.95),
        RealParameter("lifetime T1", 30,50),
        RealParameter("lifetime T2", 15,40),
        RealParameter("lifetime T3", 15,40),
        RealParameter("lifetime T4", 15,40),
        RealParameter("ec gr t1", 0.03,0.035),
        RealParameter("ec gr t2", -0.01,0.03),
        RealParameter("ec gr t3", -0.01,0.03),
        RealParameter("ec gr t4", -0.01,0.03),
        RealParameter("ec gr t5", -0.01,0.03),
        RealParameter("ec gr t6", -0.01,0.03),
        RealParameter("ec gr t7", -0.01,0.03),
        RealParameter("ec gr t8", -0.01,0.03),
```

```
        RealParameter("ec gr t9", -0.01,0.03),
        RealParameter("ec gr t10", -0.01,0.03),
        RealParameter("random PR min", 0.9,1),
        RealParameter("random PR max", 1,1.1),
        IntegerParameter("seed PR T1", 1,100),
        IntegerParameter("seed PR T2", 1,100),
        IntegerParameter("seed PR T3", 1,100),
        IntegerParameter("seed PR T4", 1,100),
        RealParameter("absolute preference for MIC", 2,5),
        RealParameter("absolute preference for expected cost per MWe",2,5),
        RealParameter("absolute preference against unknown",1,3),
        RealParameter("absolute preference for expected progress",1,3),
        RealParameter("absolute preference against specific CO2 emissions",2,5),
        CategoricalParameter("SWITCH preference for MIC", (0,1), default = 1),
        CategoricalParameter("SWITCH preference for expected cost per MWe", (0,1), default = 1),
CategoricalParameter("SWITCH preference against unknown", (0,1), default=1),
CategoricalParameter("SWITCH preference for expected progress",(0,1),default=1),
CategoricalParameter("SWITCH preference against specific CO2 emissions",(0,1)),
        RealParameter("performance expected cost per MWe T1",1,2),
        RealParameter("performance expected cost per MWe T2",1,5),
        RealParameter("performance expected cost per MWe T3",1,5),
        RealParameter("performance expected cost per MWe T4",1,5),
        RealParameter("performance CO2 avoidance T1",4,5),
        RealParameter("performance CO2 avoidance T2",1,4),
        RealParameter("performance CO2 avoidance T3",1,4),
        RealParameter("performance CO2 avoidance T4",1,4),
        CategoricalParameter("SWITCH T3", (0,1), default=0 ),
        CategoricalParameter("SWITCH T4", (0,1), default=0 ),
        CategoricalParameter("order lifetime T1", (1,3,10,1000), default = 3),
        CategoricalParameter("order lifetime T2", (1,3,10,1000), default = 3),
        CategoricalParameter("order lifetime T3", (1,3,10,1000), default = 3),
        CategoricalParameter("order lifetime T4", (1,3,10,1000), default = 3),]
ensemble = ModelEnsemble()
ensemble.model_structures = model
policies = [Policy('no policy',
model_file=..\models\ESDMAElecTrans_NoPolicy.vpm'),
        Policy('static policy',         model_file='..\models\ESDMAElecTrans_StaticPolicy.vpm'),
        Policy('adaptive policy',       model_file='..\models\ESDMAElecTrans_AdaptivePolicy.vpm') ]
ensemble.policies = policies

ensemble.parallel = True
nr_runs = 5000
results  = ensemble.perform_experiments(nr_runs)
fn = './data/FTA {} experiments.tar.gz'.format(nr_runs)
save_results(results, fn)
```

Feature scoring algorithm on simulations without policy

```
import ema_workbench.analysis.feature_scoring as feature_scoring

if __name__ == '__main__':
    fn = './data/FTA 5000 experiments without policy.tar.gz'.format(nr_runs)
    experiments, outcomes = load_results(fn)
    x = experiments, y = outcomes
    fs = feature_scoring.get_feature_scores_all(x, y)
    i=0
    for row in fs['total fraction new technologies'].values:
        print(fs['total fraction new technologies'].index[i])
        print (row)
        i=i+1
```

CART algorithm on simulations without policy

```
import ema_workbench.analysis.cart as cart

def classify(data):
    result = data['total fraction new technologies']
    classes =  np.zeros(result.shape[0])
    classes[result[:, -1] < 0.4] = 1
    return classes

if __name__ == '__main__':
```

```
    fn = './data/FTA 5000 experiments without policy.tar.gz'.format(nr_runs)
    results = load_results(fn)
    cart_alg = cart.setup_cart(results, classify, incl_unc=[
        "ini cap T1","ini cap T2","ini cap T3","ini cap T4",
        "ini cost T1","ini cost T2","ini cost T3","ini cost T4",
        "ini cum decom cap T1","ini cum decom cap T2","ini cum decom cap T3","ini cum decom cap T4",
        "average planning and construction period T1","average planning and construction period
        T2","average planning and construction period T3","average planning and construction period
        T4",
        "ini PR T1","ini PR T2","ini PR T3","ini PR T4",
        "lifetime T1","lifetime T2","lifetime T3","lifetime T4",
        "absolute preference for MIC","absolute preference for expected cost per MWe","absolute
        preference against unknown","absolute preference for expected progress","absolute preference
        against specific CO2 emissions",
        "performance expected cost per MWe T1","performance expected cost per MWe T2","performance
        expected cost per MWe T3","performance expected cost per MWe T4",
        "performance CO2 avoidance T1","performance CO2 avoidance T2","performance CO2 avoidance
        T3","performance CO2 avoidance T4",
        "SWITCH T3","SWITCH T4"], mass_min=0.05)
    cart_alg.build_tree()
    print (cart_alg.stats_to_dataframe())
    print (cart_alg.boxes_to_dataframe().T)
    cart_alg.display_boxes(together=False)
    plt.show()
```

PRIM algorithm on simulations without policy

```
import ema_workbench.analysis.prim as prim
from sympy.polys.rationaltools import together

def classify(data):
    result = data['total fraction new technologies']
    classes =  np.zeros(result.shape[0])
    classes[result[:, -1] < 0.4] = 1
    return classes

if __name__ == '__main__':
    fn = './data/FTA 5000 experiments without policy.tar.gz'.format(nr_runs)
    results = load_results(fn)
    experiments, results = results
    prim_obj = prim.setup_prim(results, classify, threshold=0.5, threshold_type=1)
    box_1 = prim_obj.find_box()
    box_1.inspect(style='graph')
    box_1.write_ppt_to_stdout()
    print(prim_obj.stats_to_dataframe()), print(prim_obj.boxes_to_dataframe())
    prim_obj.display_boxes(together=False), plt.show()
```

PRIM algorithm on static policy runs where the fraction of new technologies is below 40% and above 80%

```
# the fraction of new technologies is below 40%
def classify(data):
    result = data['total fraction new technologies']
    classes =  np.zeros(result.shape[0])
    classes[result[:, -1] < 0.4] = 1
    return classes
# the fraction of new technologies is above 80%
def classify(data):
    result = data['total fraction new technologies']
    classes =  np.zeros(result.shape[0])
    classes[result[:, -1] > 0.8] = 1
    return classes

if __name__ == '__main__':
    fn = './data/FTA 5000 experiments without policy.tar.gz'.format(nr_runs)
    results = load_results(fn)
    experiments, results = results

    logicalIndex = experiments['policy'] == 'static policy'
    newExperiments = experiments[ logicalIndex ]
    newResults = {}
    for key, value in results.items():
        newResults[key] = value[logicalIndex]
```

```
    results = (newExperiments, newResults)
    prim_obj = prim.setup_prim(results, classify, threshold=0.5, threshold_type=1)
    box_1 = prim_obj.find_box(), box_1.inspect(style='graph')
    box_1.write_ppt_to_stdout()
    print(prim_obj.stats_to_dataframe()), print(prim_obj.boxes_to_dataframe())

    prim_obj.display_boxes(together=False)
    plt.show()
```

Chapter 3:

10000 simulations without policy, basic policy, adaptive policy

```
from __future__ import division
from expWorkbench import SimpleModelEnsemble, CategoricalUncertainty,\
                         ParameterUncertainty, save_results, Outcome

import expWorkbench.EMAlogging as logging
from expWorkbench.vensim import VensimModelStructureInterface

class EnergyTrans(VensimModelStructureInterface):
    def __init__(self, workingDirectory, name):
        """interface to the model"""
        super(EnergyTrans, self).__init__(workingDirectory, name )
        self.modelFile = r'\ESDMAElecTrans_NoPolicy.vpm'
        #outcomes
       self.outcomes.append(Outcome('total fraction new technologies' , time=True))
       self.outcomes.append(Outcome('installed capacity T1' , time=True))
       self.outcomes.append(Outcome('installed capacity T2' , time=True))
       self.outcomes.append(Outcome('installed capacity T3' , time=True))
       self.outcomes.append(Outcome('installed capacity T4' , time=True))
       self.outcomes.append(Outcome('total capacity installed' , time=True))
       #Initial values
    self.uncertainties.append(ParameterUncertainty((14000,16000), "ini cap T1")) #
    self.uncertainties.append(ParameterUncertainty((1,2), "ini cap T2")) #
    self.uncertainties.append(ParameterUncertainty((1,2), "ini cap T3")) #
    self.uncertainties.append(ParameterUncertainty((1,2), "ini cap T4")) #
self.uncertainties.append(ParameterUncertainty((5e6,15e6), "ini cost T1"))
self.uncertainties.append(ParameterUncertainty((5e6, 1e7), "ini cost T2"))
self.uncertainties.append(ParameterUncertainty((5e6, 1e7), "ini cost T3"))
self.uncertainties.append(ParameterUncertainty((5e6, 1e7), "ini cost T4"))
self.uncertainties.append(ParameterUncertainty((5e6,1e7), "ini cum decom cap T1"))
self.uncertainties.append(ParameterUncertainty((1,100), "ini cum decom cap T2"))
self.uncertainties.append(ParameterUncertainty((1,100), "ini cum decom cap T3"))
self.uncertainties.append(ParameterUncertainty((1,100), "ini cum decom cap T4"))
self.uncertainties.append(ParameterUncertainty((1,5), "average planning and construction period T1"))
self.uncertainties.append(ParameterUncertainty((1,5), "average planning and construction period T2"))
self.uncertainties.append(ParameterUncertainty((1,5), "average planning and construction period T3"))
self.uncertainties.append(ParameterUncertainty((1,5), "average planning and construction period T4"))
        self.uncertainties.append(ParameterUncertainty((0.85,0.95), "ini PR T1"))
        self.uncertainties.append(ParameterUncertainty((0.7,0.95), "ini PR T2"))
        self.uncertainties.append(ParameterUncertainty((0.7,0.95), "ini PR T3"))
        self.uncertainties.append(ParameterUncertainty((0.7,0.95), "ini PR T4"))
        #Plain Parametric Uncertainties
        self.uncertainties.append(ParameterUncertainty((30,50), "lifetime T1"))
        self.uncertainties.append(ParameterUncertainty((15,40), "lifetime T2"))
        self.uncertainties.append(ParameterUncertainty((15,40), "lifetime T3"))
        self.uncertainties.append(ParameterUncertainty((15,40), "lifetime T4"))
        #One uncertain development over time -- smoothed afterwards
self.uncertainties.append(ParameterUncertainty((0.03,0.035), "ec gr t1")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t2")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t3")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t4")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t5")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t6")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t7")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t8")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t9")) #0.03
self.uncertainties.append(ParameterUncertainty((-0.01,0.03), "ec gr t10")) #0.03
        #Uncertainties in Random Functions
        self.uncertainties.append(ParameterUncertainty((0.9,1), "random PR min"))
        self.uncertainties.append(ParameterUncertainty((1,1.1), "random PR max"))
```

```python
self.uncertainties.append(ParameterUncertainty((1,100), "seed PR T1", integer=True))
self.uncertainties.append(ParameterUncertainty((1,100), "seed PR T2", integer=True))
self.uncertainties.append(ParameterUncertainty((1,100), "seed PR T3", integer=True))
self.uncertainties.append(ParameterUncertainty((1,100), "seed PR T4", integer=True))
#Uncertainties in Preference Functions
self.uncertainties.append(ParameterUncertainty((2,5), "absolute preference for MIC"))
self.uncertainties.append(ParameterUncertainty((1,3), "absolute preference for expected cost per MWe"))
self.uncertainties.append(ParameterUncertainty((2,5), "absolute preference against unknown"))
self.uncertainties.append(ParameterUncertainty((1,3), "absolute preference for expected progress"))
self.uncertainties.append(ParameterUncertainty((2,5), "absolute prf against specific CO2 emissions"))
self.uncertainties.append(CategoricalUncertainty((0,1), "SWITCH prf for MIC", default = 1))
self.uncertainties.append(CategoricalUncertainty((0,1), "SWITCH prf for expcost per MWe", default = 0))
self.uncertainties.append(CategoricalUncertainty((0,1), "SWITCH prf against unknown", default = 0))
self.uncertainties.append(CategoricalUncertainty((0,1), "SWITCH prf for exp progress", default = 0))
self.uncertainties.append(CategoricalUncertainty((0,1), "SWITCH prf agnst CO2 emissions", default = 0))
self.uncertainties.append(ParameterUncertainty((1,2), "performance expected cost per MWe T1"))
self.uncertainties.append(ParameterUncertainty((1,5), "performance expected cost per MWe T2"))
self.uncertainties.append(ParameterUncertainty((1,5), "performance expected cost per MWe T3"))
self.uncertainties.append(ParameterUncertainty((1,5), "performance expected cost per MWe T4"))
self.uncertainties.append(ParameterUncertainty((4,5), "performance CO2 avoidance T1"))
self.uncertainties.append(ParameterUncertainty((1,5), "performance CO2 avoidance T2"))
self.uncertainties.append(ParameterUncertainty((1,5), "performance CO2 avoidance T3"))
self.uncertainties.append(ParameterUncertainty((1,5), "performance CO2 avoidance T4"))
#Switches op technologies
self.uncertainties.append(ParameterUncertainty((0,1), "SWITCH T3", integer=True))
self.uncertainties.append(ParameterUncertainty((0,1), "SWITCH T4", integer=True))
#ORDERS OF DELAYS
self.uncertainties.append(CategoricalUncertainty((1,3,10,1000), "order lifetime T1", default = 3))
self.uncertainties.append(CategoricalUncertainty((1,3,10,1000), "order lifetime T2", default = 3))
self.uncertainties.append(CategoricalUncertainty((1,3,10,1000), "order lifetime T3", default = 3))
self.uncertainties.append(CategoricalUncertainty((1,3,10,1000), "order lifetime T4", default = 3))

    def model_init(self, policy, kwargs):
        try:
            self.modelFile = policy['file']
        except:
            logging.debug("no policy specified")
        super(EnergyTrans, self).model_init(policy, kwargs)


if __name__ == "__main__":
    logger = logging.log_to_stderr(logging.INFO)
    model = EnergyTrans(r'..\..\models\EnergyTrans', "ESDMAElecTrans")
    model.step = 4 #reduce data to be stored
    ensemble = SimpleModelEnsemble()
    ensemble.set_model_structure(model)

    policies = [{'name': 'no policy',
                 'file': r'\ESDMAElecTrans_NoPolicy.vpm'},
                {'name': 'basic policy',
                 'file': r'\ESDMAElecTrans_basic_policy.vpm'},
                {'name': 'adaptive policy',
                 'file': r'\ESDMAElecTrans_ap_with_op.vpm'},
                ]
    ensemble.add_policies(policies)
    ensemble.parallel = True
    results = ensemble.perform_experiments(10000)
    save_results(results, 'TFSC_all_policies.cPickle')
```

PRIM algorithm on no policy runs where the fraction of new technologies is above 60%

```python
def classify(data):
    result = data['total fraction new technologies']
    classes =  np.zeros(result.shape[0])
    classes[result[:, -1] > 0.6] = 1
    return classes

#load data
results = load_results('TFSC_all_policies.cPickle')
cases,results=results
logicalIndex = cases['policy']=='no policy'
newCases = cases[logicalIndex]
#newCases = newCases[1000:2000]
newResults = {}
```

```
for key, value in results.items():
    value = value[logicalIndex]
    newResults[key] = value[:,:]
results = (newCases, newResults)
#perform prim on selected outcome
boxes = prim.perform_prim(results, classify,threshold=0.7, threshold_type=1)

prim.write_prim_to_stdout(boxes)
prim.show_boxes_individually(boxes, results)
plt.show()
```

Chapter 4:

Robustness Check

```
import cPickle
import numpy as np
from expWorkbench.util import load_optimization_results
from deap.benchmarks.tools import convergence
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
import matplotlib as mpl
from expWorkbench import load_results, MINIMIZE, MAXIMIZE
from deap import creator, base
from analysis.b_and_w_plotting import set_fig_to_bw

weights = (MAXIMIZE, MAXIMIZE, MINIMIZE)
creator.create("Fitness", base.Fitness, weights=weights)
creator.create("Individual", dict, fitness=creator.Fitness) #@UndefinedVariable
data, pop, cases =
load_optimization_results(r'..\cPickles\MultiObjRobOpt\SIMPAT_80gen_200pop_500cases.cPickle', weights)

data = data.change
data1 = []
data2 = []
data3 = []

for entry in data:
    data1.append(entry[0] + entry[1])
    data2.append(entry[0])
    data3.append(entry[1])

change = data.change
change = np.asarray(change)

fig = plt.figure()
ax = fig.add_subplot(111)
ax.plot(data1)
ax.plot(data2)
ax.plot(data3)

ax.set_xlabel("generations")
ax.set_ylabel("nr. of changes to pareto front")

ax.plot(change[:, 0], label='added')
ax.plot(change[:, 1], label='removed')
ax.legend(loc='best')
ax.set_xlabel("# of generations")
ax.set_ylabel("# of changes")

fig = set_fig_to_bw(fig)
plt.show()
```

Setup and execute robust optimization

```
class SIMPAT_Opt(VensimModelStructureInterface):
    #outcomes
    outcomes = [
                Outcome('cumulative carbon emissions', time=True),
                Outcome('carbon emissions reduction fraction', time=True),
                Outcome('fraction renewables', time=True),
```

```
                Outcome('average total costs', time=True),
                Outcome('total costs of electricity', time=True),
                ]
    #Plain Parametric Uncertainties
    uncertainties = [ParameterUncertainty((0.9,1.1),"year"),#1
         ParameterUncertainty((0,0.5),"demand fuel price elasticity factor"),#0.25
         ParameterUncertainty((30,50),"economic lifetime biomass"),#40
         ParameterUncertainty((30,50),"economic lifetime coal"),#40
         ParameterUncertainty((25,40),"economic lifetime gas"),#30
         ParameterUncertainty((30,50),"economic lifetime igcc"),#40
         ParameterUncertainty((25,40),"economic lifetime ngcc"),#30
         ParameterUncertainty((50,70),"economic lifetime nuclear"),#60
         ParameterUncertainty((20,30),"economic lifetime pv"),#25
         ParameterUncertainty((20,30),"economic lifetime wind"),#25
         ParameterUncertainty((50,70),"economic lifetime hydro"),#60
         ParameterUncertainty((0.5,1.5),"uncertainty initial gross fuel costs"),#1
         ParameterUncertainty((0.5,4),"investment proportionality constant"),#1
ParameterUncertainty((0.2,2),"investors desired excess capacity investment"),#0.5
ParameterUncertainty((-0.07,-0.001),"price demand elasticity factor"),#-0.05
ParameterUncertainty((0.1,0.2),"price volatility global resource markets"),#0.2
ParameterUncertainty((0.85,1),"progress ratio biomass"),#0.915
ParameterUncertainty((0.9,1.05),"progress ratio coal"),#0.95
ParameterUncertainty((0.85,1),"progress ratio gas"),#0.915
ParameterUncertainty((0.9,1.05),"progress ratio igcc"),#0.95
ParameterUncertainty((0.85,1),"progress ratio ngcc"),#0.915
ParameterUncertainty((0.9,1.05),"progress ratio nuclear"),#0.95
ParameterUncertainty((0.75,0.9),"progress ratio pv"),#0.80
ParameterUncertainty((0.85,1),"progress ratio wind"),#0.915
ParameterUncertainty((0.9,1.05),"progress ratio hydro"),#0.9
ParameterUncertainty((0.1,3),"starting construction time"),#1
ParameterUncertainty((2013,2100),"time of nuclear power plant ban"),#2060
ParameterUncertainty((1,10),"weight factor carbon abatement"),#5
ParameterUncertainty((1,10),"weight factor marginal investment costs"),#5
ParameterUncertainty((1,10),"weight factor technological familiarity"),#5
ParameterUncertainty((1,10),"weight factor technological growth potential"),#5
ParameterUncertainty((0.2,3),"maximum battery storage uncertainty constant"),#1
ParameterUncertainty((0.2,0.6),"maximum no storage penetration rate wind"),
ParameterUncertainty((0.1,0.4),"maximum no storage penetration rate pv"),#0.15
#### "Categorical Uncertainty"
CategoricalUncertainty((1,2,3,4),"SWITCH lookup curve TGC", default=1),
CategoricalUncertainty((1,2),"SWITCH preference carbon curve", default=1),
CategoricalUncertainty((1,2,3,4,5,6),"SWITCH economic growth", default=2),
CategoricalUncertainty((1,2,3,4,5,6),"SWITCH electrification rate", default=2),
CategoricalUncertainty((1,2),"SWITCH Market price determination", default=1),
CategoricalUncertainty((1,2),"SWITCH physical limits", default=1),
CategoricalUncertainty((1,2,3,4),"SWITCH low reserve margin price markup"),
CategoricalUncertainty((1,2,3,4),"SWITCH interconnection capacity expansion"),
CategoricalUncertainty((1,2,3,4,5,6,7),"SWITCH storage for intermittent supply"),
CategoricalUncertainty((1,2,3),"SWITCH carbon cap", default=2),
CategoricalUncertainty((1,2,3),"SWITCH TGC obligation curve", default=2),
CategoricalUncertainty((1,2,3),"SWITCH carbon price determination", default=2),

model_file = r'\RB_V25_ets_1_policy_modified_adaptive_extended_outcomes.vpm'

    def model_init(self, policy, kwargs):
        '''initializes the model'''
        ema_logging.debug("starting to run policy: %s" % (policy['name']))
        self.policy = policy
        self.policy.pop('name')
        super(SIMPAT_Opt, self).model_init(policy, kwargs)

    def run_model(self,case):
        for key, value in self.policy.iteritems():
            case[key] = value
        super(SIMPAT_Opt, self).run_model(case)

def perform_robust_optimization():
    def obj_func(outcomes):
        average = np.average(outcomes["fraction renewables"][:, -1])
        stdev = np.std(outcomes["fraction renewables"][:,-1])
        score_1 = (average+1) / (stdev+1)
       average = np.average(outcomes["carbon emissions reduction fraction"][:,-1])
       stdev = np.std(outcomes["carbon emissions reduction fraction"][:,-1])
       score_2 = (average+1) / (stdev+1)
```

```python
        average = np.average(outcomes["average total costs"][:,-1])
        stdev = np.std(outcomes["average total costs"][:,-1])
        score_3 = (average+1) * (stdev+1)

        return score_1, score_2, score_3

    ema_logging.log_to_stderr(ema_logging.INFO)

    model = SIMPAT_Opt(r'..\models', "SIMPAT_Opt")
    ensemble = ModelEnsemble()
    ensemble.set_model_structure(model)
    ensemble.parallel = True

    policy_levers = {'Desired Fraction': {'type':'range', 'values':[0.5,1.0]},
                     'AddComm': {'type':'range', 'values':[0.0,0.75]},
                     'subsidy factor': {'type':'range', 'values':[0.0,0.5]},
                     'subsidy duration': {'type':'range', 'values':[0,20]},
                     'Proximity': {'type':'range', 'values':[1.0,2.0]},
                     "trigger": {'type':'range', 'values':[0.0,1.0]},
                     "decommission factor": {'type':'range', 'values':[0.0,0.5]},
                     "TimeAhead": {'type':'range', 'values':[10,40]} }
    samples = ensemble._generate_samples(500, UNION)[0]
    ensemble.add_policy({"name":None})
    experiments = [entry for entry in ensemble._generate_experiments(samples)]
    for entry in experiments:
        entry.pop("model")
        entry.pop("policy")
    cases = experiments

stats_callback, pop = ensemble.perform_robust_optimization(cases=cases,
  reporting_interval=1000, obj_function=obj_func, weights = (MAXIMIZE, MAXIMIZE,
  MINIMIZE), nr_of_generations=50, pop_size=200, crossover_rate=0.8,
  mutation_rate=0.05, policy_levers=policy_levers )

save_results((stats_callback, pop, cases),
r'..\cPickles\MultiObjRobOpt\SIMPAT_50gen_200pop_500cases.cPickle')

def test_model():
    workdir = "..\models"
    ema_logging.log_to_stderr(ema_logging.INFO)
    random.seed(100)
    def generate_random_policies(nr_of_policies):
        policies = [{'name': 'RB no ETS 1',
         'file': r'\RB_V25_no_ets_1_extended_outcomes.vpm'},
         {'name': 'RB ETS 1',
         'file': r'\RB_V25_ets_1_extended_outcomes.vpm'},
         {'name': 'RB Basic Policy ETS 1',
         'file': r'\RB_V25_ets_1_policy_modified_extended_outcomes.vpm'},
         {'name': 'RB Adaptive Policy ETS 1',
         'file': r'\RB_V25_ets_1_policy_modified_adaptive_extended_outcomes.vpm'}]

        for i in range(nr_of_policies):
            name = 'Random Policy ' + str(i)
            policy = {"name": name,
                      "Desired Fraction": float(random.randrange(5,10))/10,
                      "AddComm": float(random.randrange(0,75)/100),
                      "subsidy factor": float(random.randrange(0,5)/10),
                      "subsidy duration": random.randrange(0,50),
                      "Proximity": float(random.randrange(10,20)/10),
                      "trigger": random.random(),
                      "decommission factor": random.random(),
                      'file': r'\RB_V25_ets_1_policy_modified_extended_outcomes.vpm'}
            policies.append(policy)
        return policies
    policies= generate_random_policies(10)
    model = SIMPAT_Opt(workdir, "SIMPAT_Opt")
    model.step_size = 16
    ensemble = ModelEnsemble(MonteCarloSampler())
    ensemble.set_model_structure(model)
    ensemble.add_policies(policies)
    results = ensemble.perform_experiments(1000, reporting_interval=100)
save_results(results, r'..\cPickles\MultiObjRobOpt\RobustnessCheck1000.cPickle')
```

```python
if __name__ == '__main__':
    perform_robust_optimization()
```

Changes to the Pareto front over the generations

```python
weights = (MAXIMIZE, MAXIMIZE, MINIMIZE)
creator.create("Fitness", base.Fitness, weights=weights)
creator.create("Individual", dict, fitness=creator.Fitness)
data, pop, cases =
load_optimization_results(r'..\cPickles\MultiObjRobOpt\SIMPAT_80gen_200pop_500cases.cPickle', weights)

data = data.change
data1 = []
data2 = []
data3 = []

for entry in data:
    data1.append(entry[0] + entry[1])
    data2.append(entry[0])
    data3.append(entry[1])

change = data.change
change = np.asarray(change)

fig = plt.figure()
ax = fig.add_subplot(111)
ax.plot(data1)
ax.plot(data2)
ax.plot(data3)

ax.set_xlabel("generations")
ax.set_ylabel("nr. of changes to pareto front")

ax.plot(change[:, 0], label='added')
ax.plot(change[:, 1], label='removed')
ax.legend(loc='best')
ax.set_xlabel("# of generations")
ax.set_ylabel("# of changes")

fig = set_fig_to_bw(fig)
plt.show()
```

Non-Pareto solutions and Pareto solution in 3D

```python
weights = (MAXIMIZE, MAXIMIZE, MINIMIZE)
creator.create("Fitness", base.Fitness, weights=weights)
creator.create("Individual", dict, fitness=creator.Fitness)

stats_callback, pop, cases =
load_results(r'..\cPickles\MultiObjRobOpt\SIMPAT_80gen_200pop_500cases.cPickle')

hof = stats_callback.hall_of_fame
entries = set()
for entry in hof:
    entries.add(entry['name'])
    print entry

from analysis.pairs_plotting import pairs_scatter, pairs_density
data = np.zeros((len(hof), 3))

for i, entry in enumerate(hof):
    data[i,:] = entry.fitness.values

nonpareto = stats_callback.stats
non_pareto_solutions = np.zeros((len(nonpareto), 3))
for i, entry in enumerate(nonpareto):
    non_pareto_solutions[i] = entry

to = {"Renewable Fraction robustness": data[:, 0],
      "CO2 Reduction robustness": data[:, 1],
      "Average Costs robustness": data[:, 2]}
te = np.zeros(len(hof,), dtype=[('a', np.float)])
tr = (te, to)
```

```
fig1, axes = pairs_scatter(tr, filter_scalar=False)
fig1.set_figheight(10)
fig1.set_figwidth(10)

fig2, axes = pairs_density(tr, filter_scalar=False)
fig2.set_figheight(10)
fig2.set_figwidth(10)

pareto = data
nonpareto = non_pareto_solutions

max1= np.max(pareto[:,0])
max2= np.max(pareto[:,1])
max3= np.max(pareto[:,2])

min1= np.min(pareto[:,0])
min2= np.min(pareto[:,1])
min3= np.min(pareto[:,2])

max11= np.max(nonpareto[:,0])
max12= np.max(nonpareto[:,1])
max13= np.max(nonpareto[:,2])

min11= np.min(nonpareto[:,0])
min12= np.min(nonpareto[:,1])
min13= np.min(nonpareto[:,2])

max1 = max(max1,max11)
max2 = max(max2,max12)
max3 = max(max3,max13)

min1 = min(min1,min11)
min2 = min(min2,min12)
min3 = min(min3,min13)

fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

ax.w_xaxis.set_pane_color((1.0, 1.0, 1.0, 1.0))
ax.w_yaxis.set_pane_color((1.0, 1.0, 1.0, 1.0))
ax.w_zaxis.set_pane_color((1.0, 1.0, 1.0, 1.0))
ax.scatter(pareto[:,0], pareto[:,1], pareto[:,2], c='k')


x1 = ((nonpareto[:,0]-min1)/(max1-min1))
x2 = ((pareto[:,0]-min1)/(max1-min1))
y1 = ((nonpareto[:,1]-min2)/(max2-min2))
y2 = ((pareto[:,1]-min2)/(max2-min2))
z1 = ((nonpareto[:,2]-min3)/(max3-min3))
z2 = ((pareto[:,2]-min3)/(max3-min3))

ax.set_xlabel('Renewable Fraction robustness')
ax.set_ylabel('CO2 Reduction robustness')
ax.set_zlabel('Average Costs robustness')
ax.set_xbound(lower=0, upper=1)
ax.set_ybound(lower=0, upper=1)
ax.set_zbound(lower=0, upper=1)

pareto_solutions = []
for entry in hof:
    pareto_solutions.append(entry.fitness.values)
pareto_solutions = np.array(pareto_solutions)
non_pareto_solutions = []
for entry in stats_callback.stats:
    non_pareto_solutions.append(entry)
non_pareto_solutions = np.array(non_pareto_solutions)

imagine1 = np.zeros(len(pareto_solutions[:, 0]))
non_imagine1 = np.zeros(len(non_pareto_solutions[:, 0]))
imagine2 = np.zeros(len(pareto_solutions[:, 0]))
non_imagine2 = np.zeros(len(non_pareto_solutions[:, 0]))
imagine2 = imagine2 + 1
non_imagine2 = non_imagine2 + 1
```

```
cset = ax.scatter(x2, y2, imagine1, color='0.75',s=4, alpha=0.1)
cset = ax.scatter(x2, imagine2, z2, color='0.75',s=4, alpha=0.1)
cset = ax.scatter(imagine1, y2, z2, color='0.75',s=4, alpha=0.1)

cset = ax.scatter(x1, y1, non_imagine1, color='0.75',s=4, alpha=0.1)
cset = ax.scatter(x1, non_imagine2, z1, color='0.75',s=4, alpha=0.1)
cset = ax.scatter(non_imagine1, y1, z1, color='0.75',s=4, alpha=0.1)

fig.set_figwidth(10)
fig.set_figheight(10)
plt.show()
```

Comparison of Adaptive and three optimized policies

```
class SIMPAT_Opt(VensimModelStructureInterface):
    #outcomes
    outcomes = [Outcome('cumulative carbon emissions', time=True),
                Outcome('carbon emissions reduction fraction', time=True),
                Outcome('fraction renewables', time=True),
                Outcome('average total costs', time=True),
                Outcome('total costs of electricity', time=True),]
    #Plain Parametric Uncertainties
uncertainties=[ParameterUncertainty((0.9,1.1),"year"),#1
ParameterUncertainty((0,0.5),"demand fuel price elasticity factor"),#0.25
ParameterUncertainty((30,50),"economic lifetime biomass"),#40
ParameterUncertainty((30,50),"economic lifetime coal"),#40
ParameterUncertainty((25,40),"economic lifetime gas"),#30
ParameterUncertainty((30,50),"economic lifetime igcc"),#40
ParameterUncertainty((25,40),"economic lifetime ngcc"),#30
ParameterUncertainty((50,70),"economic lifetime nuclear"),#60
ParameterUncertainty((20,30),"economic lifetime pv"),#25
ParameterUncertainty((20,30),"economic lifetime wind"),#25
ParameterUncertainty((50,70),"economic lifetime hydro"),#60
ParameterUncertainty((0.5,1.5),"uncertainty initial gross fuel costs"),#1
ParameterUncertainty((0.5,4),"investment proportionality constant"),#1
ParameterUncertainty((0.2,2),"investors desired excess capacity investment"),#0.5
ParameterUncertainty((-0.07,-0.001),"price demand elasticity factor"),#-0.05
ParameterUncertainty((0.1,0.2),"price volatility global resource markets"),#0.2
ParameterUncertainty((0.85,1),"progress ratio biomass"),#0.915
ParameterUncertainty((0.9,1.05),"progress ratio coal"),#0.95
ParameterUncertainty((0.85,1),"progress ratio gas"),#0.915
ParameterUncertainty((0.9,1.05),"progress ratio igcc"),#0.95
ParameterUncertainty((0.85,1),"progress ratio ngcc"),#0.915
ParameterUncertainty((0.9,1.05),"progress ratio nuclear"),#0.95
ParameterUncertainty((0.75,0.9),"progress ratio pv"),#0.80
ParameterUncertainty((0.85,1),"progress ratio wind"),#0.915
ParameterUncertainty((0.9,1.05),"progress ratio hydro"),#0.9
ParameterUncertainty((0.1,3),"starting construction time"),#1
ParameterUncertainty((2013,2100),"time of nuclear power plant ban"),#2060
ParameterUncertainty((1,10),"weight factor carbon abatement"),#5
ParameterUncertainty((1,10),"weight factor marginal investment costs"),#5
ParameterUncertainty((1,10),"weight factor technological familiarity"),#5
ParameterUncertainty((1,10),"weight factor technological growth potential"),#5
ParameterUncertainty((0.2,3),"maximum battery storage uncertainty constant"),#1
ParameterUncertainty((0.2,0.6),"maximum no storage penetration rate wind"),#0.22
ParameterUncertainty((0.1,0.4),"maximum no storage penetration rate pv"),#0.15
#### "Categorical Uncertainty"
CategoricalUncertainty((1,2,3,4),"SWITCH lookup curve TGC", default=1),
CategoricalUncertainty((1,2),"SWTICH preference carbon curve", default=1),
CategoricalUncertainty((1,2,3,4,5,6),"SWITCH economic growth", default=2),
CategoricalUncertainty((1,2,3,4,5,6),"SWITCH electrification rate", default=2),
CategoricalUncertainty((1,2),"SWITCH Market price determination", default=1),
CategoricalUncertainty((1,2),"SWITCH physical limits", default=1),
CategoricalUncertainty((1,2,3,4),"SWITCH low reserve margin price markup"),
CategoricalUncertainty((1,2,3,4),"SWITCH interconnection capacity expansion"),
CategoricalUncertainty((1,2,3,4,5,6,7),"SWITCH storage for intermittent supply"),
CategoricalUncertainty((1,2,3),"SWITCH carbon cap", default=2),
CategoricalUncertainty((1,2,3),"SWITCH TGC obligation curve", default=2),
CategoricalUncertainty((1,2,3),"SWITCH carbon price determination", default=2),]

model_file = r'\SIMPAT_Adaptive.vpm'
    def model_init(self, policy, kwargs):
        '''initializes the model'''
```

```python
        super(SIMPAT_Opt, self).model_init(policy, kwargs)
        try:
            self.model_file = policy['file']
        except KeyError:
            ema_logging.warning("key 'file' not found in policy")
            policy = copy.copy(policy)
            policy.pop('name')
            for key, value in policy.items():
                vensim.set_value(key, value)
            self.model_file = r'\SIMPAT_Adaptive.vpm'
if __name__ == "__main__":
    ema_logging.log_to_stderr(ema_logging.INFO)
    model = SIMPAT_Opt(r'..\models\SIMPAT', "SIMPAT_Opt")
    ensemble =  ModelEnsemble()
    ensemble.set_model_structure(model)
    policies = [{'name': 'Adaptive Policy',
                 'file': r'\SIMPAT_Adaptive.vpm'},
                {'name': 'Optimized Policy 0',
                 'file': r'\SIMPAT_Optimized_0.vpm'},
                {'name': 'Optimized Policy 1',
                 'file': r'\SIMPAT_Optimized_1.vpm'},
                {'name': 'Optimized Policy 2',
                 'file': r'\SIMPAT_Optimized_2.vpm'},
                {'name': 'Optimized Policy 3',
                 'file': r'\SIMPAT_Optimized_3.vpm'}]
    ensemble.add_policies(policies)
    ensemble.parallel = True #turn on parallel processing
    results = load_results(r'..\cPickles\SIMPAT_OPTIMIZED_POLICIES_10000.cPickle')
    outcomes = ['carbon emissions reduction fraction','fraction renewables',
                'average total costs']
    titles = {'carbon emissions reduction fraction': 'CO2 reduction fraction',
              'fraction renewables': 'Renewables fraction',
              'average total costs':'Average costs'}
    ylabels = {'carbon emissions reduction fraction': 'CO2 reduction fraction',
              'fraction renewables': 'Renewables fraction',
              'average total costs':'Average costs'}
    fig, axes = envelopes(results, density=KDE, group_by= 'policy',
                          outcomes_to_show=outcomes, fill=True,
                          titles=titles, ylabels=ylabels,
        grouping_specifiers=['Adaptive Policy','Optimized Policy 1'
                                 ,'Optimized Policy 2', 'Optimized Policy 3'] )

    minima = {}
    maxima = {}
    for key, value in results[1].items():
        minima[key] = np.min(value)
        maxima[key] = np.max(value)
    log=True
    colormap = 'gray'
    fig, axes = simple_kde(results, outcomes, colormap,
                           log, minima, maxima)
    plt.show()
```

Executive Summary

Policymaking often involves different parties such as policymakers, stakeholders, and analysts each with distinct roles in the process. To assist policymakers, policy analysts help in structuring the problem, designing, and evaluating policy alternatives. Analysts face many challenges, like complexity and uncertainty in a system of interest, while supporting the policymaking process. Frequently, analysts rely on mathematical models that represent the key features of the system. Models aim to represent the real world as a mathematical explanation, and inevitably possess many pre-analytic and analytic assumptions like parameter estimates, model structures, and worldviews. These assumptions made during modelling introduce a significant level of uncertainty in the models, and forecasting based on models is therefore always bound by this uncertainty. Therefore, instead of focusing on limited best-estimate predictions under uncertainty, exploring a plethora of plausible futures by using mathematical models can be a better approach to support decision-making.

In current practice, uncertainty analysis for decision-making is mostly limited to technical and shallow uncertainties about model parameters, input data, or initial states. However, there are deeper uncertainties involved in decision-making where information and awareness about such uncertainties are scarce. Deep uncertainty prevails 'where analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes' (Lempert et al., 2003). Deep uncertainty confronts decision-making processes and makes them more complex and difficult. There is an urgent and crucial need to develop and improve methods and techniques to handle deep uncertainty, both for analysts and decision makers. This thesis contributes to a solution for enhanced handling of deep uncertainty to support policymaking. We have developed a new methodological approach for improving analytical support for policymaking under deep uncertainty, and demonstrated each analytical advancement stage with case studies. The methodology aims to assist development of adaptive and robust policies.

Especially in the presence of deep uncertainty, where reliable assumptions about the future cannot be made, the use of models as predictive tools is very prone to result in misleading results under deep uncertainty. However, the use of models for decision support in an exploratory manner- exploring a collection of plausible futures- instead of focusing on a limited set of futures offers a strong answer. Exploratory Modeling and Analysis (EMA) uses mathematical models for analyzing dynamically complex issues under uncertainty. EMA utilizes computational experiments to provide insights and understanding about system's functioning and about the effectiveness/robustness of policies under a wide set of different assumptions. In contrast to predictive modelling, where a single best estimate model is used as a surrogate for the actual system, EMA explores the uncertainty space, analyzing the output extensively for better guidance to develop adaptive policies.

Grasping useful insights from the resulting immense input and output spaces can strongly benefit from analytical techniques like pattern analysis, and data mining. Despite the difficulty of such techniques, they can assist and improve model-based policymaking using EMA.

Using a System Dynamics model about the competition of four different energy technologies, we evaluate three analytical techniques for improving EMA. Feature scoring shows which uncertainties have more importance in terms of the impact on the outcome(s) of interest. Classification and Regression Trees (CART) is a machine-learning method to create subsets of the uncertainty space in terms of decision trees. The Patient Rule Induction Method (PRIM) is a data-mining algorithm to find also subset(s) in the input space that results in the desired output space. We use such data analysis algorithms/techniques in combination with EMA as an approach to explore the energy transitions model. The resulting analysis of different policies reveals that, for this case, a dynamic policy performs better than a static policy for stimulating a future development of new sustainable energy technologies. This provides an indication that dynamic policymaking may be better than static policies under deep uncertainty more in general.

How to embed these analytical techniques within a step-wise approach for supporting policy design? We present an iterative model-based approach for designing adaptive policies that are robust under deep uncertainty. In essence, the Adaptive Robust Design (ARD) approach, as we call it, operationalizes Adaptive Policymaking in terms of EMA using the three analytical techniques. ARD therefore utilizes EMA in the context of adaptive policymaking in a stepwise manner to identify and address both vulnerabilities and opportunities resulting in an adaptive robust policy. We illustrate the approach by means of a long-term policymaking case related to the transition of the energy system toward sustainability. The dynamic, complex, and deeply uncertain nature of energy systems make them a challenging case for adaptive policymaking. Our analysis illustrates that the ARD approach can be used to develop long-term, adaptive and robust policies for grand societal transformations.

Besides dealing with dynamic complexity and deep uncertainty, policymaking for most complex adaptive systems requires handling a multi-actor process. In reality, policymaking has to deal with multiple and possibly conflicting objectives. We therefore develop an approach to use multi-objective robust optimization in the context of adaptive policymaking. We use multi-objective robust optimization to address the question when, i.e. for what trigger values, to adapt a policy. Robust optimization addresses the uncertainty, while multi-objective optimization aids the consideration of multiple conflicting objectives. We demonstrate this approach by further improving the policy developed earlier by fine tuning the conditions under which to adapt the policy.

To conclude, this thesis proposes to improve analytical support for policymaking to better handle deep uncertainty. Building upon the existing pragmatic practice, a systematic approach for designing adaptive policies under uncertainty is developed. Research questions addressed in all chapters build up to the main statement of this thesis: The Adaptive Robust Design approach in combination with multi-objective robust optimization will improve the support for policymaking under deep uncertainty. The effectiveness of ARD for developing adaptive robust policies under deep uncertainty is shown by illustrative case studies. The key focus and contribution of this study is methodological, and the presented approach can be applied to any system of interest where mathematical models are available. The field of policymaking under uncertainty will face numerous new and exciting challenges, one of which will definitely be about exploring deep structural uncertainty on models of the system of interest. The multi-disciplinary nature of policymaking under uncertainty makes communication and collaboration the keywords for the future of this field; researchers will only reach new horizons by sharing their ideas and expertise within and among scientific societies. The exploration of new analytical techniques and the collaboration with multi-disciplinary researchers will help develop new analytical methods and techniques for supporting policymaking. In addition to the variety of existing approaches, this list of new methods and techniques should be categorized according to which method or technique is more suitable for the problem of interest. Such a categorization can be used as a guidebook for policy analysts to help select methods and techniques when faced with different policy problems. Furthermore, this guidebook categorization can provide advanced assistance for policy analysts and avoid potential miscommunication between analysts and policymakers by creating transparency on methods used by policy analysts.

Samenvatting

Tijdens beleidsontwikkeling zijn in de regel verschillende partijen betrokken met elk een unieke rol: beleidsmakers, stakeholders, en beleidsanalisten. Beleidsanalisten ondersteunen beleidsmakers met de probleemstructurering en het ontwerpen en beoordelen van beleidsopties. De analisten moeten hierbij omgaan met diverse uitdagingen, waaronder de complexiteit en onzekerheid van het bestudeerde beleidssysteem. Wiskundige modellen van het gedrag van de belangrijkste aspecten van het systeem zijn hierbij een veel gebruikt hulpmiddel. Deze modellen zijn onvermijdelijk gestoeld op allerlei aannames met betrekking tot onder andere parameterwaardes, specifieke wiskundige vergelijkingen, modelstructuur en wereldbeelden. Al deze aannames dragen bij aan de onzekerheid in het model. Verwachtingen op basis van dit soort modellen zijn daardoor intrinsiek onzeker. In plaats van te proberen deze onzekerheid te reduceren, kan deze expliciet geaccepteerd en meegenomen worden in de beleidsanalyse door het modelmatig verkennen van vele mogelijke toekomsten.

Onzekerheidsanalyse is in de gangbare praktijk meestal beperkt tot slechts het analyseren van relatief technische onzekerheden rondom modelparameters, inputdata en initiële waarden. Er zijn echter allerlei diepere onzekerheden die mogelijk veel relevanter zouden kunnen zijn voor de besluitvorming waar betrokkenen zich niet van bewust zijn. Er is sprake van diepe onzekerheid als de analist en/of de partijen betrokken bij de besluitvorming het niet eens kunnen worden over (1) de juiste conceptualisatie van de relaties van essentiële drijvende factoren die de toekomst bepalen; (2) de kansverdelingen die gebruikt worden om de onzekerheid in variabelen en model parameters te representeren; en/of (3) de wenselijkheid van verschillende uitkomsten (Lempert, Popper, & Bankes, 2003). Diepe onzekerheid bemoeilijkt besluitvormingsprocessen. Zowel beleidsanalisten als beleidsmakers hebben veel baat bij de ontwikkeling van methoden en technieken die om kunnen gaan met diepe onzekerheid. Dit proefschrift levert op dit vlak een bijdrage. Ik beschrijf hier de ontwikkeling van een nieuwe, methodische aanpak voor het verbeteren van de analytische ondersteuning van beleidsontwikkeling onder diepe onzekerheid, geïllustreerd aan de hand van een aantal casestudies. Het doel van de ontwikkelde methodische aanpak is het ondersteunen van de ontwikkeling van adaptief en robuust beleid.

Diepe onzekerheid maakt het doen van betrouwbare aannames over de toekomst en daarmee voorspellend gebruik van wiskundige modellen zeer riskant. Het gebruik van dit soort modellen op een verkennende manier daarentegen, waarbij een grote verzameling van mogelijke toekomsten wordt onderzocht, is buitengewoon nuttig. In Hoofdstuk 2 illustreer ik het gebruik van verkennend modelleren voor het analyseren van dynamische, complexe vraagstukken onder diepe onzekerheid. Verkennend modelleren gebruikt computer experimenten om inzicht te krijgen in hoe het systeem functioneert onder verschillende aannamen en wat de effectiviteit en robuustheid is van beleidsopties. In tegenstelling tot voorspellend modelleren, waar een één beste schatting gebruikt wordt, wordt bij verkennend modelleren systematisch de gehele onzekerheidsruimte verkend. De resultaten van deze verkenning worden uitgebreid geanalyseerd ter ondersteuning van de ontwikkeling van adaptief beleid. Om nuttige inzichten te kunnen opdoen uit deze enorme ruimtes van modelinput en -output kunnen analytische technieken zoals patroonherkenning en data mining gebruikt worden, ook al is de toepassing van deze technieken verre van triviaal.

Met behulp van een casestudie over de ontwikkeling van vier concurrerende energietechnologieën heb ik drie analytische technieken voor het verbeteren van verkennend modelleren toegepast. De eerste techniek, Feature scoring, laat zien welke onzekerheden meer of juist minder invloed hebben op de modeluitkomsten. De tweede techniek, Classification and Regression Trees (CART), is een methode van machinaal leren voor het maken van deelruimtes in de onzekerheidsruimte met behulp van beslisbomen. De derde techniek, de Patient Rule Induction Method (PRIM), is een data-minings algoritme om deelruimtes in de onzekerheidsruimte te vinden die resulteren in uitkomsten waarin de analist geïnteresseerd is. Ik heb deze drie technieken in een casestudy gebruikt om adaptief beleid te ontwikkelen voor de energietransitie. Het adaptieve beleid werkt aantoonbaar beter dan statisch beleid in het realiseren van een duurzame toekomst. Dit geeft aanleiding tot de verwachting dat onder diepe onzekerheid adaptief beleid in zijn algemeenheid beter zou kunnen functioneren dan statisch beleid.

Een volgende stap is het inpassen van de drie onderzochte analytische technieken in een stapsgewijze aanpak voor het ondersteunen van beleidsontwerp. In hoofdstuk 3 presenteer ik een iteratieve, modelgebaseerde aanpak voor het ontwerpen van adaptief beleid dat tevens robuust is. In de basis is Adaptive Robust Design, zoals ik het noem, een uitwerking van het ontwerpproces van adaptief beleid met behulp van verkennend modelleren met gebruik van de drie analytische technieken. Adaptive Robust Design gebruikt op een stapsgewijze manier verkennend modelleren om kwetsbaarheden en kansen te identificeren om deze vervolgens te vertalen naar acties die onderdeel zijn van adaptief, robuust beleid. Ik illustreer deze aanpak met een case van beleidsontwikkeling op de lange termijn voor de transitie van het energiesysteem naar duurzaamheid. Mijn analyse laat zien dat Adaptive Robust Design bruikbaar is voor het ontwikkelen, van adaptief en robuust beleid voor grootschalige sociale transformaties met oog op de lange termijn.

Een belangrijke dimensie van beleidsontwikkeling, naast het omgaan met dynamische complexiteit en diepe onzekerheid, is het zogenaamde multi-actorproces. Tijdens de ontwikkeling van beleid dient rekening gehouden te worden met verschillende, dikwijls conflicterende doelen en belangen. In Hoofdstuk 4 presenteer ik hoe Multi-Objective Robust Optimalisation gebruikt kan worden ter ondersteuning van adaptief beleidsontwerp. Ik gebruik Multi-Objective Robust Optimalisation als hulpmiddel om te bepalen onder welke condities adaptief beleid aangepast moet worden. Robuuste optimalisatie is een manier om rekening te houden met de diepe onzekerheid, terwijl multi-objective optimalisatie rekening houdt met de verschillende belangen en doelen. Ik demonstreer dit door voort te bouwen op de case uit hoofdstuk 3.

Samenvattend: De ambitie van dit proefschrift is om bij een bijdrage te leveren aan het verbeteren van de analytische ondersteuning voor beleidsontwikkeling in het omgaan met diepe onzekerheid. Ik heb hiervoor een systematische aanpak ontwikkeld voor het ontwerpen van adaptief beleid onder diepe onzekerheid die voortbouwt op de huidige, pragmatische aanpak. De centrale stelling is hierbij dat Adaptive Robust Design in combinatie met multi-objective robust optimalisation zal bijdragen aan beleidsontwikkeling onder diepe onzekerheid. De effectiviteit van deze benadering is gedemonstreerd in illustratieve casestudies. De focus en bijdrage van deze dissertatie is expliciet methodisch van aard. De gepresenteerde aanpak is dan ook in principe van toepassing op elk beleidsprobleem waar mathematische modellen gebruikt worden in de beleidsontwikkeling.

Onderzoek naar de ondersteuning van beleidsontwerp onder diepe onzekerheid bevat echter nog een aantal grote uitdagingen. Een hele belangrijke uitdaging is hoe omgegaan kan worden met diepe onzekerheid over de structuur van een model. Voorts zullen, vanwege het multidisciplinaire karakter van het onderzoeksveld communicatie en samenwerking essentieel zijn. Nieuwe doorbraken kunnen alleen gerealiseerd worden door ideeën te delen met en tussen bestaande wetenschappelijke gemeenschappen. Een andere onderzoeksrichting is inzicht te krijgen in welke analytische technieken voor verkennend modelleren het beste passen bij welk type probleem. Een dergelijk overzicht kan beleidsanalisten helpen in het kiezen van de juiste technieken gegeven de aard van het beleidsprobleem waar ze aan werken. Daarnaast zal het bijdragen aan het verminderen van miscommunicatie tussen analisten en beleidsmakers, en de transparantie van de gevolgde aanpak verhogen.

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List of publications

Articles in peer-reviewed journals

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About the Author

Caner Hamarat was born on November 5, 1984 in Zonguldak, Turkey. Following his high school education at Zonguldak Science High School (ZFL) in 2002, he obtained his B.Sc. degree in Manufacturing Systems Engineering in 2007 and his M.Sc. degree in Industrial Engineering in 2009 at Sabanci University in Istanbul. Then, he started his Ph.D. studies at the Policy Analysis section of Delft University of Technology in 2010 under the supervision of Prof.dr.ir Wil A.H. Thissen and Dr. Erik Pruyt. By the end of his Ph.D contract in 2014, Caner started to work as business analyst for Ricoh Europe SCM in Bergen op Zoom. After 5 great years at Ricoh, he joined Rabobank Data Analytics team as a data analyst in February 2019. At the same time he was working, he finished writing this thesis.

His research interests include but not limited to Exploratory Modelling and Analysis, uncertainty analysis, Adaptive Policymaking, optimization, advanced data analysis methods. Currently, he works at Rabobank in Utrecht as data analyst since February 2019.

Besides his academic and business life, he enjoys traveling and cycling long tours with his lovely wife Nalan, practicing yoga, and playing guitar for an exclusive audience, who is mostly only his wife.

The Adaptive Robust Design Approach
Improving Analytical Support under Deep Uncertainty

Policymaking often involves different parties such as policymakers, stakeholders, and analysts each with distinct roles in the process. To assist policymakers, policy analysts help in structuring the problem, designing, and evaluating policy alternatives. Analysts face many challenges, like complexity and uncertainty in a system of interest, while supporting the policymaking process. Frequently, analysts rely on mathematical models that represent the key features of the system. Assumptions made during modelling introduce a significant level of uncertainty in the models, and forecasting based on models is therefore always bound by this uncertainty. Instead of focusing on limited best-estimate predictions under uncertainty, exploring a plethora of plausible futures by using mathematical models can help supporting decision-making.

In current practice, uncertainty analysis for decision-making is mostly limited to technical and shallow uncertainties but not focused on deep uncertainty. This thesis contributes to a solution for enhanced handling of deep uncertainty to support policymaking. We have developed a new methodological approach for improving analytical support for policymaking under deep uncertainty, and demonstrated each analytical advancement stage with case studies.

This thesis proposes to improve analytical support for policymaking to better handle deep uncertainty. Building upon the existing pragmatic practice, a systematic approach for designing adaptive policies under uncertainty is developed. The Adaptive Robust Design (ARD) approach in combination with multi-objective robust optimization will improve the support for policymaking under deep uncertainty. The effectiveness of ARD for developing adaptive robust policies under deep uncertainty is shown by illustrative case studies.

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